THREE ESSAYS ON THE RELATIONSHIP BETWEEN ECONOMIC DEVELOPMENT AND ENVIRONMENTAL QUALITY

A Dissertation

by

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ABSTRACT

This thesis is concerned with examining the relationship between indicators of economic growth and environmental quality. During this process, the analysis explores and attempts to interlink the following theoretical and empirical frameworks: Angelsen and Kaimowitz’s theories for deforestation, the Environmental Kuznets Curve (EKC) hypothesis and the forest transition theory. Macro-level data are used to examine the implications of these frameworks. The implications of the first essay suggest that different crops have a different impact on rate of change of agricultural land use. The second analysis suggests that the results from a Directed Acyclical Graph Approach present a uni-directional causal relationship between income and pollution emissions. The third and final essay suggests that property rights structures and economic incentives appear to be the most probable explanations for the forest transition in India. The macro-level nature of the data sets employed provides information on the broad trends and patterns. For policy recommendations, a more detailed and specific analysis needs to be carried out concentrating on a certain region.

DEDICATION

To my grandmothers Janaki Ramiah and Padma Natarajan.

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NOMENCLATURE

AK	Angelsen and Kaimowitz
DV	Dijkgraaf and Vollebergh
GR	Green Revolution
JFM	Joint Forest Management
SC	Stern and Common

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CHAPTER I

INTRODUCTION

This thesis is divided into three essays. They are all concerned with environmental degradation at the macro level. The first essay examines the impact of the Green Revolution (GR) on the rate of change of agricultural extent. An increase in the agricultural area is considered to be a proxy for an increase in deforested area. The second essay is concerned with measuring the nature of causality between pollution and income in the context for the Environmental Kuznets Curve (EKC). The third and final essay is an examination of the forest transition in India; focusing on the possible role of two policies.

Essay #1 The Impact of the Green Revolution on the Rate of Change of Land Use

This chapter examines the impact of the GR on the rate of change of agricultural land extent. The initial goal was to examine the effect of the GR on the rate of deforestation. However, due to the lack of reliable data, a change in the rate of agricultural extent is considered to be a proxy for a change in the rate of deforestation.

The GR is defined as the complex combination of advanced agricultural technologies: (i) improved seed or planting materials; (ii) chemical fertilizers and (iii) irrigation. The impact of these changes on the forest cover is not clear. Various theories have been formulated to explain the impact of these changes. In this chapter we analyze the extent to which these alternative theories are consistent with the international data.

The first of these theories is known as the Borlaug Hypothesis, after Norman Borlaug who, along with others, has asserted that the GR could solve the problem of tropical deforestation by reducing the need for extensive agriculture as cereal demand increases rise (World Resources Institute 1986; Rudel and Horowitz 1993; Southgate 1998; Rudel 2001). Angelsen and Kaimowitz's (2001) theoretical framework derives the impact of various types of technological change on deforestation under differing market conditions. They find that the impact of technical change is not uniform. One of the implications of their model, tested in this analysis, is that the impact of technical progress is dependent upon the sector in which the change occurred. Technological change in the extensive sector generally leads to greater increases in deforestation when compared to the intensive sector.

A positive sign for the coefficient of percent change in cereal yield per unit land, in the regression, provides support for the Borlaug hypothesis. It implies that significant increases in cereal yield per unit of land leads to land being released for other activities such as deforestation. Empirical support for Angelsen and Kaimowitz's (2001) theory is provided if the impact of increases in rice yield is significantly lower than the impact of increases in wheat or maize yield. This is based on the premise that rice is a more labor-intensive crop when compared to either wheat or maize.

Using this theoretical structure and following Barbier's (2001) empirical specification, we test for the effect of increases in rice, wheat and maize yields on agricultural extent. This effect is tested for in various specifications of the model. In the combined specification of the model, in which all countries are considered, little support is found for Angelsen and Kaimowitz's theory; the null hypothesis that rice yield has an equal or more positive impact on agricultural land extent is not rejected when compared to wheat yield in any of the specifications. Limited support is found for the Borlaug Hypothesis.

Essay #2 Causality in the Context of the Environmental Kuznets Curve

This chapter offers a methodological contribution in the analysis of causality within the context of the Environmental Kuznets Curve (EKC). The inverted U-shaped hypothesis between various indicators of environmental degradation and income per capita, otherwise known as the EKC, has gained immense popularity over the past twenty years.

The empirical analysis of the EKC relationship is usually provided by panel data methods where the two principle explanatory variables of interest are income and income squared. A possible drawback to such cross-country panel data methods is that a certain causal structure is implicitly assumed. Directed Acyclical Graphs (DAGs) is a method that reveals the underlying causality structure among the variables included in a regression, thereby helping overcome the problems of endogeneity in some models. Frequently employed techniques such as Granger causality tests are also computed to examine the causal structures between emissions and income.

DAGs using directed edges provide a pictorial representation of all five relationships possible between any two variables X and Y. They are: there is no causal relationship; X causes Y; Y causes X; Y and X simultaneously cause each other; and the causal relationship cannot be determined by the information provided (Wang and Bessler 2005). Relationships between any two variables considered in the regression are represented; therefore, it is possible to infer the causal link between variables included in a regression.

The relationship between different emissions and income across the world is the focus of this analysis. The air pollutants of interest based on previous literature are sulfur dioxide and carbon dioxide. Therefore, the regression models employed by Stern (2010) and Harbaugh et al. (2002) are replicated to understand the relationship between variables that are normally considered within an EKC analysis.

In this chapter, we first review time series issues that are integral to establishing causality between variables; also we discuss how these issues have been dealt with within past EKC literature. We then use the DAG methodical framework to examine if it reveals any new insights into the causality between variables. We find that GDP per capita causes emissions in contemporaneous time. We then compare and contrast the results from this approach to results from Granger Causality (this approach is the effect of lagged values). Both approaches combined are necessary to understand causality as defined by Hume.

Essay #3 Examining the Role of the Social Forestry Program and the JFM Program in the Indian Forest Transition

The third essay in this dissertation considers the forest transition process in India and evaluates two forestry programs that were designed to encourage the expansion of forest lands in the country. The Forest Transition Theory (Angelsen 2007) predicts the various changes in forest cover over time. Four main stages are identified: (1) initially high forest cover and low deforestation; (2) accelerating and high deforestation; (3) slow-down of deforestation and forest cover stabilization; and (4) a period of reforestation (Angelsen 2007).

According to Mather (2007), India has gone through a forest transition and has moved from net deforestation to net reforestation. Further, the percentage of land under forest has increased. Various theories to explain the forest transition have been proposed. The relative merit of each of these theories is explored within the context of the Indian forest transition.

Historically, most of the forest in India is state owned; local populations have had historically little say in the management of these forests. Two schemes that have been instituted to promote greater participation by the locals are the Joint Forest Management scheme (JFM) and Social Forestry Program. The aim of this analysis is to examine the possible role of the Social Forestry and JFM programs in the Indian forest transition. The goal of the Social Forestry Program is to promote growth of forest products demanded by the local population on generally non-forest lands. The goal of the JFM scheme, on the other hand, is to promote greater community participation in the management of forest areas.

CHAPTER II

THE IMPACT OF THE GREEN REVOLUTION ON THE RATE OF CHANGE OF LAND USE

Introduction[1]

The significant increases in agricultural productivity commonly known as the Green Revolution (GR) spread rapidly across developing countries in Asia and Latin America, and the resultant increases in food production pulled the region back from famine and led to regional food surpluses within 25 years. It led to a decline in poverty rates, made important contributions to economic growth in the region and transformed the nature of agricultural technology by improving inputs such as irrigation, seeds, fertilizers and pesticides. It allowed countries to achieve self-sufficiency and food security (Hazell 2009).

The GR in this context refers to a series of research, development and technology transfer initiatives that increased agriculture production around the world between the 1940s and the 1970s. More specifically, it refers to the introduction of high-yielding seeds and the increased use of fertilizers and irrigation. This led to rapid increases in wheat and rice yields that, in turn, increased the per capita food availability and reduced the price of food staples (Hazell 2009). However, the environmental impact of the GR is difficult to comprehend. Of particular concern is the GR's impact on the

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[1] An earlier version of this manuscript was presented as a poster at the American Environmental and Resource Economics Association's Conference in Seattle June 2011

extent of agricultural land and, by extension, the effect on forest area. Various hypotheses have been formulated to predict the impact of this change in agricultural technology on tropical deforestation, the most notable being the Borlaug hypothesis; Norman Borlaug along with others believed that significant increases in the land productivity of cereals would lead to a decrease in tropical deforestation by reducing the need to expand the area of cultivated land as a demand for crops. Therefore, according to this argument, the GR saved large areas of forest wetlands and other fragile lands from conversion to cropping (Hazell 2009).

However, a number of concerns have been raised about the possible environmental effects of the GR. According to (Cassman 1999), increases in agricultural productivity are primarily results of four technological advancements: improved germplasm, increased fertilizer use, double cropping and irrigation (Brady and Sohngen 2008). Increased fertilizer use and double cropping could have an adverse impact on soil fertility, leading to greater soil degradation, creating incentives for more extensive uses of land which eventually lead to land being cleared away for cropping.

Furthermore, technological change does not always yield the same impact on agricultural area. As Angelsen and Kaimowitz (2001) show in their model, the intensity of the crop as well as the type of technological change is also of significance. The impact of these changes might not be uniform across all crops affected by the GR. The three crops that will be considered in this analysis are rice, wheat and maize. The labor intensities of these crops are different: rice production is far more labor intensive than either wheat or maize. Moreover, the intensities of inputs vary over time.

Objectives of this Study

The objective of this chapter is to explore the nature of the relationship between rates of agricultural expansion and increasing agricultural productivity (a result of the GR) in certain developing countries in Asia and Latin America. The indirect goal is to study the impact of increased yields on deforestation. However, data on agricultural area appear to be more reliable than the data on forest area (Barbier 2001). Therefore, the direct goal of this study is to determine if the increases in agricultural yield that resulted from the GR led to a reduction in the land area dedicated to agriculture, freeing up land for alternative activities, where one of the alternate uses of this land could be forestry. The analysis will be carried out at the national level across countries in Asia and Latin America.

Literature Review

There are many deforestation studies that also examine the impact of agricultural progress on the forestry sector. These models are divided into analytical, simulation and empirical regression models (Angelsen and Kaimowitz 1999).

The lack of reliable data in developing countries appears to be the main obstacle to empirical analyses of the impact of the GR on the forestry sector. Therefore, studies from developed countries are often used to provide insights into this phenomenon. Rudel (2001) finds evidence for the Borlaug Hypothesis in the American South, and similarities between developing and developed countries are drawn. These results are said to be general and can be extended to developing countries. Further empirical support is provided by experiences across many of the developed countries. This has led to the formulation of the following transition theory: land transitions from forest to agricultural land due to deforestation; however, with the passage of time and increasing agricultural reforestation, only lands with the greatest agricultural potential are cultivated (Mather and Needle 1998).

Jayasuriya (2001) finds that the relationship between technical progress and forest cover varies. His analysis is based on the Hecksher Ohlin framework, in which three types of land use are considered: upland agriculture, lowland agriculture and forest. The impact of technological progress on deforestation depends on the sector in which it occurs. He concludes that under certain market conditions, technical progress in the intensive sector encourages afforestation, whereas similar progress in the extensive sector could lead to greater deforestation.

The advances in cereal production due to the GR did not occur contemporaneously; technological progress was staggered across the different crops. Evenson and Gollin (2003) divide the GR era into two phases: the early GR (1961–1980) and the late GR (1981–2000) periods. The early GR had the greatest impact on rice and wheat. The technologies associated with these two crops are different: rice cultivation is more intensive than wheat cultivation; returns to labor diminish more slowly for rice rather than for wheat (Vollrath 2011).

When examining the effect of increased yields, one must control for variation in a number of other variables affecting deforestation. Angelsen and Kaimowitz (1999) base their model on a synthesis of a number of studies on deforestation. Their work, on which we build on substantially in this chapter, divides the variables that affect deforestation into the immediate causes and underlying causes. Their immediate causes of deforestation are listed in table II.1. and the underlying causes are discussed at greater length in the paragraphs that follow the table.

Population pressures

With increases in population, the aggregate demand for a number of forest resources also increases. These resources include land, fuel wood, timber and other forest products; however, growing populations could also lead to technological progress and institutional change which contribute to reduced pressure on forests. Multi-country regression models find a positive correlation (e.g., Cropper and Griffiths (1994)) or no correlation, between population density and deforestation. The validity of the results from these studies is questioned by Angelsen and Kaimowitz (1999). They object to the use of forest area data from the Food and Agricultural Organization (FAO), which is considered to be unreliable. The FAO carries out forest resource assessments once every five years; estimates for intervening years are interpolated based on population data. This could be a potential source of endogeneity.

Table II.1. Major Results on Immediate Causes of Deforestation

Variable	Effect of increase in variable, by model type: Analytical	Simulation and empirical	Comments
Agricultural output prices	Increase	Increase	Farm-level analytical mdels predict increase, unless there are strong income effects (subsistence models).
Agricultural input prices	Indeterminate	Mixed	Fertilizer price increases may induce shift to more land-extensive systems.
Off-farm wages and employment	Reduce	Reduce	Among the most significant findings.
Credit availability	Indeterminate	Increase	Depends on whether the relevant investment is forest clearing or forest management and agricultural intensification; most studies find that credit finances deforestation.
Technological progress on frontier farms (direct effects)	Indeterminate	Little evidence	Similar to price increase: new labor intensive technologies may reduce deforestation if labor supply is inelastic.
Accessibility (roads)	Increase	Increase	Among the most significant findings, although roads are partly endogenous.
Homesteading property regime	Increase	Little evidence	Claims to future land rents give farmers additional incentive to clear land.
Land tenure security	Indeterminate	Increase	Empirical evidence is relatively weak.
Timber prices	Indeterminate	Increase	Empirical evidence is relatively weak but tends to find a positive link

Source: Table 2 in Angelsen and Kaimowitz (1999) pg 82 "Rethinking the causes of deforestation: lessons from economic models." *The World Bank Research Observer* 14:73–98 reproduced with permission of the Oxford University Press.

Income level

The impact of income on the forest extent is ambiguous. On one hand, higher national incomes provide nonagricultural or off-farm employment opportunities that can reduce the pressure on forest land. Increased incomes could also lead to greater awareness and desire to protect the forest. However, increased incomes also lead to an increase in demand for agricultural and forest products, which may result in increased deforestation (Angelsen and Kaimowitz 1999).

The EKC idea is extended to income and the rate of deforestation. A number of multi-country regression analyses have found empirical evidence for this hypothesis (Cropper and Griffiths 1994; Culas 2007; Bhattarai and Hammig 2001; Bhattarai and Hammig 2004). However, there are also studies that have found no such evidence (Koop and Tole 1999).

External debt trade and structural adjustment

Policies and institutional factors also have an impact on the forestry sector. Specifically, there is expected to be a positive relationship between external indebtedness and deforestation. In analytical models it is found that external indebtedness and structural adjustments increase deforestation (Angelsen and Kaimowitz 1999). Empirically, institutional factors are considered by Bhattarai and Hammig (2001) who include variables such as black market foreign exchange and debt, policies that are designed to encourage agricultural and food exports stimulate deforestation. Their model is estimated for Asia, Africa and Latin America. The sign for the debt coefficient is found to have a positive and significant sign in all three estimations, whereas, black market foreign exchange is positive and significant only for Asia.

The indirect effects of technical change

This chapter is primarily concerned with the impact of this variable. A theoretical discussion of the results of technical change will be provided in greater detail in the theoretical review section of this chapter. Initial multi-country studies did control for the effect of agricultural progress, for example Bhattarai and Hammig (2001). Culas (2007) included an agricultural production index as well as a variable that measured agricultural trend, the index was insignificant with the inclusion of the institutional variable

Barbier (2001) finds evidence that increases in cereal yield led to reductions in agricultural expansion. However, these results do not appear to be significant when indices measuring political stability, corruption and property rights are added. Barbier (2001) is also important because, rather than utilizing data on forest area, he uses data on agricultural area, which are considered to be more reliable.

The Theoretical Framework

The theoretical framework used here is based on Angelsen and Kaimowitz (2001, AK hereafter). The mathematical details associated with this model are elaborated further in the appendix. The results derived from this model are presented in table II.2. The authors consider the impact of three different types of technological progress on forest area: yield increasing technical progress (α), labor-intensive technical progress (β) and, labor-saving technical progress in the intensive sector (ε). Three types of parameters are utilized to represent the three types of technical change $\alpha, \beta, \varepsilon$. An increase in the parameter, α, represents a pure yield increasing technological change; this is known as a Hicks neutral technological change because it does not affect the marginal rate of substitution between land and labor. The implications of a neutral technological change on the rate of deforestation are the same as a price increase in outputs. Examples of this form of technology progress include the introduction of higher yielding crops and pest-resistant varieties.

An increase in the parameter β represents an increase in labor intensity. This technology is also termed land-saving technological change because it impacts the marginal rates of substitution positively; a smaller quantity of labor can be substituted for a unit of land. As well as increasing the yields per acre, this type of technological change also tends to increase the labor employed per acre of land. With this type of technological change, effective labor becomes relatively cheaper when compared to land. The farmer, therefore, tends to employ larger amounts of labor.

Table II.2. Impact of Technological Progress on Agricultural Land Extent

Type of technological progress (t.p.)	Subsistence model with imperfect markets	Farm model with perfect markets	Macro model with endogenous wages	Macro model with endogenous prices
Pure yield increasing t.p. in intensive sector (α)	NA	NA	Decrease	Decrease
Labor intensive t.p. in intensive sector (β)	NA	NA	Decrease	Decrease
Labor saving t.p. in intensive sector (ε)	NA	NA	Increase	Decrease
Pure yield increasing t.p. in extensive sector (α)	Decrease	Increase	Increase	Not known
Labor intensive t.p. in extensive sector (β)	Decrease	No effect	Decrease	Decrease
Labor saving t.p. in extensive sector (ε)	No effect	Increase	Increase	Not known

NA– not applicable. In the first two models, the agricultural sector is not divided into the intensive and extensive sectors.
Source: Table 6.2 Angelsen and Kaimowitz (2001), pg. 102 in "When does technological change in agriculture promote deforestation?" D. R. Lee and C. B. Barret, eds. in *Tradeoffs or synergies?: agricultural intensification, economic development and the environment* reproduced with the permission of CAB International, Wallingford, U.K.

The application of greater capital inputs leads to an increase in the parameter ε. This type of technological change is termed as labor-saving technological progress and decreases the amount of time required to accomplish a certain task, which typically leads to displacement of labor. This could, for example, be the use of tractors, which may be cheaper to invest in rather than labor. Agricultural labor may now find that a nonagricultural activity might provide them with better wages. Therefore, labor is diverted towards these activities.

The effect of changes in these parameters and their implications on the agricultural extent were derived and analyzed under four settings of consumer preferences and market conditions by Angelsen and Kaimowitz (2001). Two of their models are microeconomic in nature: the subsistence and the open economy models. The remainder macroeconomic: the endogenous wage and price models. The objective of the farm model and the macroeconomic models is to maximize profit, whereas, the objective of the subsistence model is to minimize effort. In the macroeconomic models, the agricultural area is divided into two: the intensive and the extensive sectors. Moreover, when compared to the farm model, the market conditions are not perfect; in one scenario the wages are endogenously determined, and in the other prices are endogenously determined.

Table II.2 summarizes theoretical results of the models, which the authors suggest might be empirically tested.The AK model implies that technological change in the intensive sector almost uniformly leads to the conservation of forests. Moreover, characteristics of the labor and the product markets involved do not seem to matter except for the case labor-saving technology which expels labor to the extensive sector. The magnitude of this effect depends on market conditions. For example, according to Southgate (1998), in the US, increases in opportunities of work in other sectors reduced the supply of agricultural labor; this generated a contraction of the area used to raise cattle and livestock (AK 2001). More specifically, with respect to the GR, AK has observed that introduction of high-yielding rice varieties and fertilizers in Asia have led to the conservation of forests in these areas. The large increases in rice production are said to have depressed rice prices, which in turn prevented families from expanding their food crops into forested areas. Coxhead and Shively (1995) test this theory using a computable general equilibrium model. They find evidence that yield improvements in maize can depress food prices, which in turn should reduce forest clearing for maize and rain-fed rice irrigation crops (AK 2001). In the empirical model tested below, rice crops will be considered as the intensive sector, whereas maize and wheat crops will be considered as the extensive sector

The effects of technological change in the extensive sector are mixed. In a subsistence economy, technological progress decreases deforestation. However, when the labor market is not constrained and the farmers are profit maximizing, technological change will increase deforestation. This prediction of the AK model will be tested by including rice trade, wheat trade and maize trade variables, where trade in crops will be regarded as a measure of the openness of the economy.

Empirical Section

The insights derived from the theoretical model will be tested using macro-level data across countries in Latin America and Asia. The specification of the empirical model is based on that used by Barbier (2001). This extension of Barbier's specification attempts to test for differences in the effect of technological change between the intensive and extensive sectors. The specific empirical hypotheses tested and their connections to the theoretical model will be discussed subsequent to the presentation of the empirical model. Table II.3 provides a brief description of and summary statistics for the variables included in this analysis.

The empirical model is summarized in equation II.1, where the dependent variable is the rate of change of agricultural extent and the independent variables are those related to the theoretical model proposed by AK:

(II.1) $\Delta A_{it}{}^{2} = \beta_c + \beta_{RY}\, RY_{it} + \beta_{WY}\, WY_{it} + \beta_{MY} MY_{it} + \beta_{PGDP}\, PGDP_{it} + \beta_{PGDP^2}\, PGDP^2{}_{it} + \beta_{PPGDP}\, PPGDP_{it} + \beta_{CRPL} CRPL_{it} + \beta_{PPON} PPON_{it} + \beta_{ARPP} ARPP_{it} + \beta_{RITR}\, RITR_{it} + \beta_{WHTR}\, WHTR_{it} + \beta_{MATR}\, MATR_{it} + U_{it}{}^{3}$

where the index i refers to a country and t refers to the year. Definitions for all variables are listed in table II.3.

[2] It is implicitly assumed that the direction of causation is unidirectional from yields to areas. This assumption is not tested. It is based on previous literature and more particularly Barbier's (2001) specification.

[3] U_{it} refers to the error term. This term contains information on variables not included in the model. In this instance these could be various socio-economic indicators that have been considered in other empirical EKC studies. However, in this instance, information on these indicators is difficult to obtain from the 1960's.

Table II.3. Summary Statistics

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
A	Arable land in km	672	8.86E+05	1.26E+06	1.81E+04	5.34E+06
RY	Rice yield per hectare in Hg	672	3.56E+04	1.51E+04	1.29E+04	7.90E+04
WY	Wheat yield per hectare in Hg	672	1.84E+04	9.79E+03	4.24E+03	5.23E+04
MY	Maize yield per hectare in Hg	672	2.05E+04	1.27E+04	3.28E+03	7.67E+04
PGDP	GDP per capita (constant 2000 US $) (centered data)	672	-2.20E-05	1.33E+03	-4.99E+03	9.29E+03
PGDPS	GDP per capita (constant 2000 US$ squared)	672	1.75E+06	7.35E+06	1.63E-02	8.63E+07
PPGDP	GDP per capita growth (annual %)	672	2.55E+00	4.40E+00	-2.64E+01	1.88E+01
CRPL	Permanent cropland (% of land area)	672	1.51E+00	1.54E+00	1.25E-01	8.80E+00
PPON	Annual percentage change in population	672	1.97E+00	7.68E-01	-1.02E+00	3.44E+00
ARPP	Arable land (hectares per person)	672	2.76E-01	2.18E-01	3.20E-02	1.10E+00
RITR	Rice export value US$ div. by inc. US$*10000	667	1.60E+00	3.57E+00	0.00E+00	2.42E+01
WHTR	Wheat export value US$ divided by income	667	6.53E-01	1.97E+00	0.00E+00	1.42E+01
MATR	Maize export value US$ divided by income	667	7.39E-01	2.25E+00	0.00E+00	2.32E+01

Empirically Testable Hypotheses

(1) Angelsen and Kaimowitz's extensive versus intensive land use hypothesis

The theoretical model provides several empirically testable hypotheses. Each of these hypotheses has been given their own name. First, the main result that emerges from AK's theoretical model is that the more labor intensive the production of a crop is, the lower the impact of technological change on agricultural expansion. Since wheat and maize are considered to be less labor intensive than rice, the model suggests that the coefficients of wheat yield and maize yield should be significantly greater than the coefficient of rice yield. This leads to our first testable hypothesis:

H1:β_{MY} and $\beta_{WY} > \beta_{RY}$,

where, β_{MY}, β_{WY} and β_{RY} are the coefficients of wheat, maize and rice.

This hypothesis is derived from the theoretical model and is based on the results from table II.3, where it is apparent that all forms of technological progress in the intensive sector, except for labor-saving technological progress in the case of models with endogenous wages, lead to a decrease in the extent of agricultural area.

(2) Borlaug hypothesis

Second, if the Borlaug effect is observed in the data, then we would expect the regression coefficient on rice, wheat and maize to be negative. This would imply that increase in yields has led to a reduction in the expansion of agricultural area. Hence, the Borlaug hypothesis can be stated formally as:

H2:β_{MY} , $\beta_{WY,}$ and $\beta_{RY} < 0$.

(3) Angelsen and Kaimowitz's profit maximization versus subsistence goal hypotheses

Another result from the theoretical model is that the more export feasible a good, the greater its positive impact on the rate of agricultural expansion. This result is based on the comparison of columns in table II.2, where the effect of technological progress on deforestation in all the market models is positive when compared to the subsistence model. We use trade volumes as indicators of a move away from the substance model towards the market model.

To isolate this affect, we include a trade index that measures the feasibility of trade of the crop. This leads to two related hypotheses. First, we can test

H3: $\beta_{\mathrm{RITR}}, \beta_{\mathrm{WHTR}}, \beta_{\mathrm{MATR}} > 0$

where, β_{RITR}, β_{WHTR}, and β_{MATR} are the coefficients on the export value relative to the nation's income for rice, wheat and maize respectively.

Further, the index of volume of trade of certain crop can be considered to be an indicator of the openness of the market of the crop. Hence, based on comparison of the columns in table II.2, it should follow that the effect on agricultural land expansion will be strongest for those crops with a higher trade index. This leads to our last testable hypothesis:

H4: $\beta_{\mathrm{RITR}} > \beta_{\mathrm{WHTR}} > \beta_{\mathrm{MATR}}$, provided rice trade >wheat trade >maize trade.

Testing for each of the hypotheses should lead to better understanding of the interlink ages between the theoretical and the empirical frameworks. Specifically, it will provide an empirical test of Angelsen and Kaimowitz's (2001) theoretical prediction that a more labor-intensive crop such as rice has less pronounced impact on agricultural expansion when compared to a less intensive crop such as wheat or maize, or the Borlaug hypothesis which states that technological progress promotes afforestation. To isolate the impact of increases in crop yields on the rate of agricultural expansion one must control for underlying factors that affect deforestation such as population pressures, income levels, trade and structural change.

Data

The variables considered in this study are mostly the same as those used by Barbier[4] (2001) and control for the underlying causes of deforestation. To control for population pressures, percentage change in population is considered, to control for income effects, variables such as annual per capita GDP growth, GDP per capita and GDP per capita squared are included. Finally, the indirect effects of technical change in agriculture are controlled for by considering yields of the various agricultural crops. In addition, variables such as percentage of land area under permanent crop and arable land per capita are also included. Rice, wheat, and maize exports and imports have been used to control for the openness of the economy.

All variables are annual from 1961 to 2008. The income variables, population variables and the data on agricultural land extent, arable land per person and percentage

[4] The variables considered by Barbier is a representation of synthesis model specification. According to Barbier a synthesis model is an integration of four types of models: Environmental Kuznets Curve analysis, competing land use models, forest land conversion models and institutional analysis. Data on institutional variables are often difficult to obtain.

of area under permanent crops are all part of the 2011 World Bank[5] Indicator data series. Percentage change in agricultural extent is calculated from the data on agricultural extent. The income data are in terms of per capita in constant 2000 U.S. dollars. Both GDP growth and population growth are in terms of annual percent change, cropland share of land is percent of total area and, finally, arable land per person is in terms of arable hectares per person.

Data on individual crops, which include rice, wheat and maize, are accessed from the FAOSTAT[6] website. The data include information on yields(FAOSTAT(2013)a) and exports, imports (FAOSTAT (2013)b) and production of these crops. Yields of the different crops are in terms of Hg/Ha. A trade index for each of the crops is created by dividing export value of each of the crops by income. The list of countries selected is based on Hazell's (2009) list of countries in Asia and Evenson and Gollin's (2003) study of the GR. The countries included in Asia are Bangladesh, China, India, South Korea, and Pakistan. And those included in the Latin American model are Argentina, Brazil, Colombia, Ecuador, Guatemala, Mexico, Peru, Paraguay and Uruguay. A combined model including 14 countries from both regions is also specified. Graphs of yields of the three crops and rate of change of agricultural area considered over time are presented below. Only a small number of countries grow all three crops, which is why the number of countries considered in this analysis is not large.

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[5] Last accessed website on 24th May 2014 from http://data.worldbank.org/data-catalog/world-development-indicators/wdi-2011. Data accessed in December 2012

[6] Last accessed website on 24th May 2014 from FAOSTAT2013a (http://faostat.fao.org/site/567/default.aspx#ancor) and FAOSTAT 2013b (.http://faostat.fao.org/site/535/default.aspx#ancor) Data accessed in December 2013.

The data series contains observations for 48–50 years across 14 countries in Latin America and Asia. The number of time periods, T, is larger than the number of countries, indicating that normal panel data methods might not be suitable. This sort of data series is known as time-series cross-section data. In a time series cross-section 1data set there are 20–50 observations over time on 10–100 units, unlike a panel data series in which there a larger number of countries and fewer time periods (Beck and Katz 1995). Figure II.1. represents rice yields across the 14 countries.

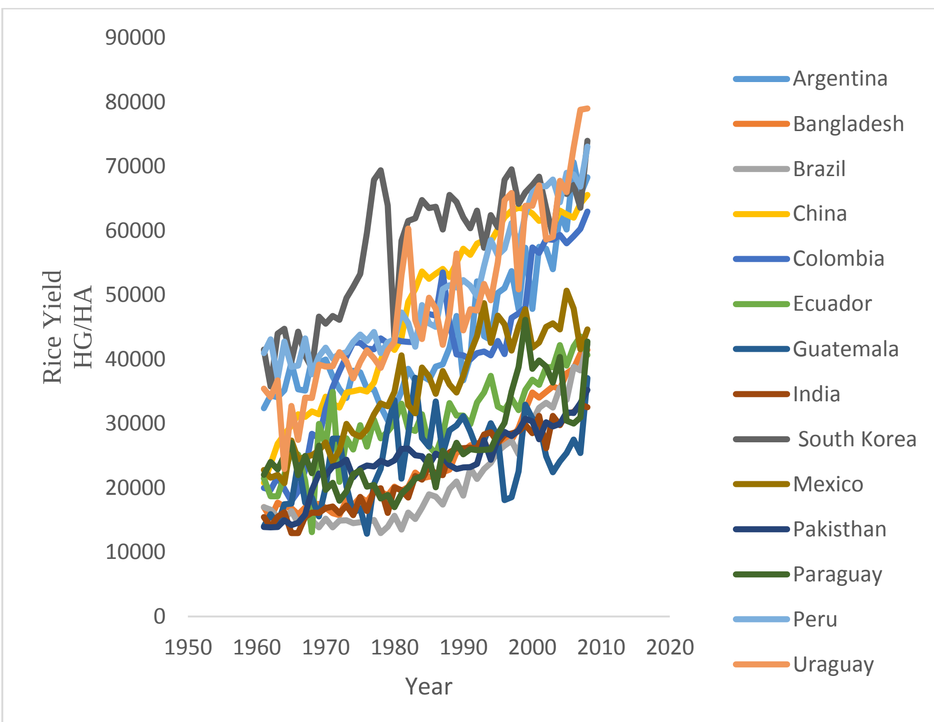

Figure II.1. Rice Yields (Hg/Ha)

Figure II.2. represents wheat yields across the 14 countries.

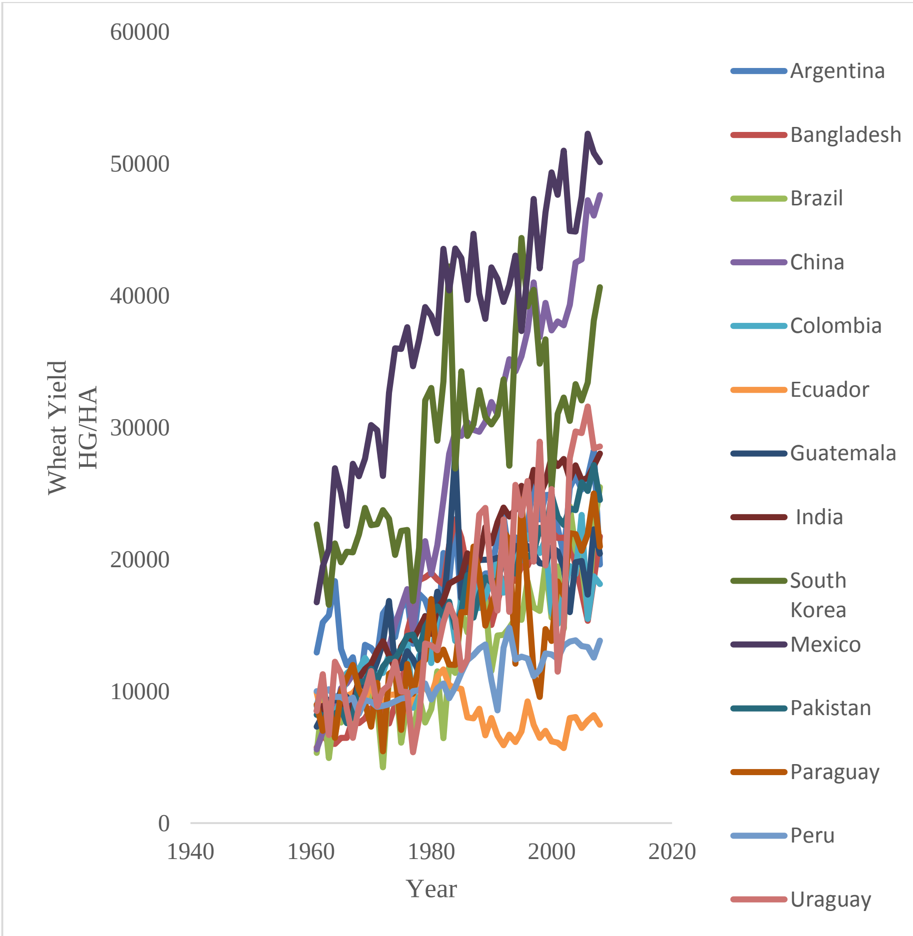

Figure II.2. Wheat Yields (Hg/Ha)

Figure II.3. represents maize yields across the 14 countries.

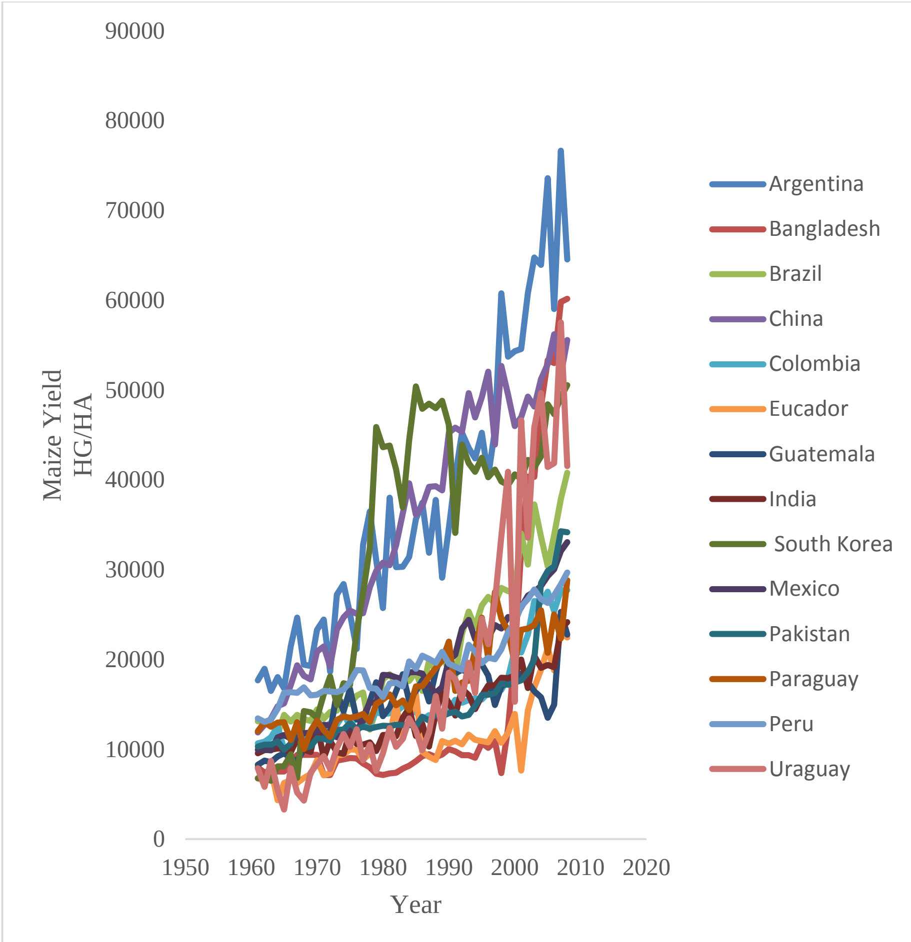

Figure II.3. Maize Yields (Hg/Ha)

Figure II.4 represents the agricultural area across the 14 countries.

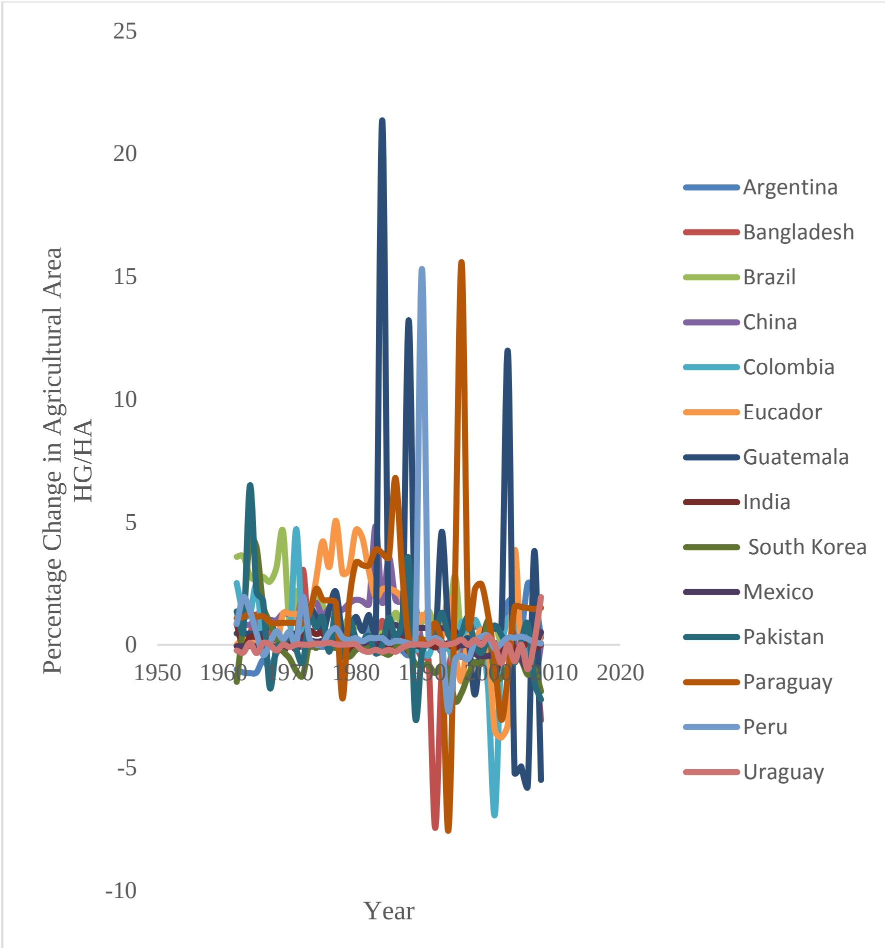

Figure II.4. Percentage Change in Agricultural Extent

Methodology

The relatively long time span of the data suggests that we must test for time-series properties such as stationarity. Non-stationarity of the data series could lead to spurious regressions and erroneous conclusions. Panel data methods that are generally employed in this area such as the fixed-effects estimator do not account for the non-stationary nature of the data. These methods are generally appropriate for data where the time span of the series is short and the number of countries sampled is large.

Stationarity and cointegration tests

In tables II.4 and II.5 we present the results of stationarity tests for all variables used. Table II.4 presents the results for the variables that come from a balanced panel, while table II. 5 presents test statistics for the variables that are unbalanced. The lag length for each series was based on the Bayesian Information Criterion (BIC), automatically computed for the Levin Lin Chu (LLC, 2002) test and the Im, Pesaran and Shin (IPS, 2003).

In table II.4 we present the results of the test LLC, the Breitung (2000) and the IPS stationarity tests. Greater details on each of these tests are provided in appendix A.II.. In each of these tests the null hypothesis is that the data are non-stationarity. All three tests are carried out since there are slight variations in each of these tests. The test statistics for the variables are presented for three groups of countries, all countries combined, just the Asian countries and just the Latin American countries. These variations have been elaborated on further in appendix A.II.. For a variable to be stationary, the null hypothesis should be rejected; the p-values associated with each of the tests are presented in tables II.4 and II.5. The choice for the LLC and IPS statistics are based on the Bayesian Information Criterion (BIC).

Table II.4. Stationarity Tests (H0: The Variable is Non-stationary, i.e., The Panels Possess at Least One Unit Root)

	Combined			Asia			Latin America		
	LLC	**IPS**	**Breitung**	**LLC**	**IPS**	**Breitung**	**LLC**	**IPS**	**Breitung**
RY	0.998	1.000	1.000	0.539	0.993	1.000	1.000	1.000	1.000
WY	0.034	0.830	1.000	0.280	0.920	1.000	0.001	0.557	0.427
MY	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000
ARPP	0.000	0.000	0.958	0.000	0.000	0.988	0.000	0.164	0.661
CRPL	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	0.998
PGDP	1.000	1.000	1.000	1.000	1.000	1.000	0.587	0.997	1.000
$PGDP^2$	1.000	1.000	0.005	1.000	1.000	0.061	0.999	0.887	0.054
PPGDP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PPON	0.968	0.994	0.757	0.949	0.974	0.168	0.941	0.955	0.999
RITR		0.000		0.916	0.000	0.138		0.000	
WHTR		0.000		0.000	0.000	0.000		0.362	
MATR		0.000		0.000	0.000	0.054		0.000	
PAGR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: RY- Rice yield per hectare in Hg; WY- Wheat yield per hectare in Hg; WY- Wheat yield per hectare in Hg; MY- Maize yield per hectare in Hg; ARPP- Arable land (hectares per person; CRPL - Permanent cropland (% of land area); PGDP-GDP per capita (constant 2000 US$) (centered) data; $PGDP^2$ -GDP per capita(constant 2000 US $) squared; PPGDP- GDP per capita growth (annual %); PPON- Annual percentage change in population; RITR Rice export value US$ divided by income: WHTR- Wheat export value US$ divided by income; MHTR- Maize export value US$ divided by income.

Table II.4 presents the results of the LLC, IPS and the Breitung tests. Both the LLC and Breitung tests can only be carried out for balanced data. However, the trade indices in the combined and Latin American models are unbalanced. Therefore, only IPS statistics are available for these variables in table II.4. Hence, in table II.5 the Fisher test statistic is also presented, which is also compatible with unbalanced data. The choice of lag length for the IPS and LLC statistics is based on the BIC criteria. The lag length for the Breitung test is based on the lag length for the LLC statistic

.

Table II.5. Stationarity Tests Using Fisher's Statistic (H0: The Variable is Non-stationary, i.e., The Panels Possess at Least One Unit Root)

	Combined	Asia	Latin America
RITR	0.000	0.020	0.000
WHTR	0.000	0.000	0.000
MATR	0.000	0.000	0.023

Notes: RITR Rice export value US$ divided by income: WHTR- Wheat export value US$ divided by income; MHTR- Maize export value US$ divided by income

Based on the results in table II.4 and table II.5, for most variables we fail to reject the null hypothesis of non-stationarity. The variables that appear to be stationary across models are the percentage change in agricultural area (PAGR) and percentage change in GDP (PPGDP). The trade indices RITR, MATR are stationary for the combined and Latin American models at the five percent level of significance. Whereas, the WHTR, the wheat trade index is stationary for the Asian and combined models.

The LLC and IPS tests in general indicate that arable land per person (ARPP) is stationary, however, the results of Breitung tests do not allow for the rejection of the null hypothesis of non-stationarity, this result is robust to lag specification. $PGDP^2$ is found to be stationary on the basis of the Breitung test; however, the LLC and IPS tests fail to reject the null hypothesis of non-stationarity, therefore this variable is also assumed to be non-stationary.

A method that accounts for the non-stationary nature of the data is the error-correction model. In order to apply the error-correction method, the data must be cointegrated. That is, a linear combination of the non-stationary variables must be stationary. Hence, we now turn to three cointegration tests whose results are presented in tables II.6, II.7 and II.8. The details associated with each of the cointegration tests carried out are also included in appendix A.II..

The variables included in the two tests of cointegration are once again rice yield (RY), wheat yield (WY), population growth (PPON), maize yield (MY), per capita GDP (PGDP) and cropland area (CRPL). Though, the variable Per Capita GDP squared ($PGDP^2$) is not stationary, it is not included in the cointegration test. The results of the Westerlund tests are presented in table II.6. The null hypothesis for these tests states that there is no cointegration amongst the variables. This method is based on error-correction models.

The results from the Westerlund test in table II.6 give no clear indication as to whether the variables are cointigrated or not. The Westerlund test is very sensitive to the specification of the test[7]. Bootstrapping is performed to provide a robust value. However, the values obtained continue to be sensitive to the specification of the model.

[7] For lags and leads greater than one, none of the Westerlund statistics reject the null hypothesis of no cointegartion. The AIC criterion may be used for choice of lag length; however, in this specification, it always led to the maximal lag length.

The panel statistic, Pt and the group statistic Gt, provide evidence that the variables are cointegrated across the combined and the Asian at the 10% level. The null hypothesis of no cointegration cannot be rejected for any statistics for the Latin American specification.

These tests do not provide a clear indication of whether the variables are cointegrated or not; therefore, additional tests for cointegration, the Kao (1999) and Pedroni (1999)[8] tests, are performed. The results of these tests are presented in tables II.7 and II.8. As seen in table II.7. below, a majority of the Pedroni statistics do not support the null hypothesis of no cointegration at the five percent level of confidence.

Table II.6. Westerlund Cointegration Tests (H0: The Variables are not Cointegrated.)

Statistic	**Value**	**Z-value**	**P-value**	**Robust P-value**
Combined				
Gt	-3.594	-1.708	0.044	0.001
Ga	-9.874	4.389	1.000	0.728
Pt	-12.593	-1.549	0.061	0.063
Pa	-8.453	3.603	1.000	0.755
Latin America				
Gt	-3.078	0.302	0.619	0.175
Ga	-10.514	3.321	1.000	0.693
Pt	-9.751	-0.894	0.186	0.118
Pa	-7.729	3.116	0.999	0.823
Asia				
Gt	-4.524	-3.263	0.001	0.000
Ga	-8.722	2.889	0.998	0.650
Pt	-8.480	-1.885	0.030	0.021
Pa	-11.298	1.487	0.931	0.131

[8] The power of these tests is often questioned since they make an assumption of common factor (McCarl et al. 2009).

Only the "panel V statistic" supports the null hypothesis of no cointegration across the three models. For the Latin American estimation, five out of the seven statistics reject the null hypothesis of no cointegration at the five percent level of significance.

Table II.7. Pedroni Cointegration Test (H0: The Variables are not Cointegrated)

	Constant		**Constant & Trend**	
	Statistic	**Prob.**	**Statistic**	**Prob.**
Combined				
Panel v-Statistic	-3.12	0.999	-4.72	1.00
Panel rho-Statistic	-4.68	0.00	-2.73	0.00
Panel PP-Statistic	-17.06	0.00	-19.11	0.00
Panel ADF-Statistic	-15.68	`0.00	-15.84	0.00
Group rho-Statistic	-3.05	0.00	-1.85	0.03
Group PP-Statistic	-18.71	0.00	-22.33	0.00
Group ADF-Statistic	-13.06	0.00	-12.72	0.00
Latin America				
Panel v-Statistic	-2.69	0.999	-3.97	1.00
Panel rho-Statistic	-3.80	0.00	-2.17	0.02
Panel PP-Statistic	-14.02	0.00	-16.08	0.00
Panel ADF-Statistic	-12.78	0.00	-12.96	0.00
Group rho-Statistic	-1.34	0.09	-0.60	0.27
Group PP-Statistic	-10.03	0.00	-16.20	0.00
Group ADF	-8.10	0.00	-8.10	0.00
Asia				
Panel v-Statistic	-0.89	0.81	-1.95	0.97
Panel rho-Statistic	-2.59	0.01	1.75	0.04
Panel PP-Statistic	-8.66	0.00	-8.63	0.00
Panel ADF-Statistic	-8.34	0.00	-8.23	0.00
Group rho-Statistic	-3.31	0.00	-2.28	0.01
Group PP-Statistic	-17.85	0.00	-15.64	0.00
Group ADF-Statistic	-10.99	0.00	-10.42	0.00

Further evidence for cointigration is provided by the results from Kao's cointegration test that are presented table II.8. Kao's cointegration test rejects the null hypothesis of no cointegration for all specifications of the model. Both the Pedroni as well as the Kao statistics provide evidence against the null hypothesis of no cointegration. Kao's test allows for the inclusion of more than six variables, therefore all trade indices and Arable land per person (ARPP) variables are included in the test.

After reviewing all of the above tests, we conclude that even though the results of the Westerlund cointegration results were inconclusive or in the case of the Latin American model did not support a hypothesis of no cointegration, a large number of statistics that make up the Pedroni test and the Kao reject the null hypothesis of no cointegration, suggesting evidence in favor of the variables being cointegrated. On the basis of this result, the error-correction method, which we now discuss, can be employed to estimate the model.

Table II.8. Kao Cointegration Tests (H0: The Variables are not Cointegrated.)

	Statistic	**Prob**
Combined		
ADF	-8.07	0.00
Latin America		
ADF	-6.14	0.00
Asia		
ADF	-7.27	0.00

The error correction model

In an error correction model, it is assumed that there is a long- run relationship between the dependent variable Y and the independent variable X. The basic structure of the error-correction model may be represented by the following equation, II.2.

(II.2) $$\Delta Y_t = \alpha + \beta \Delta X_{t-1} + EC_{t-1} + \varepsilon_t.$$

The term EC measures the speed at which the deviations from the equilibrium are corrected. This model provides us with a method of measuring both the short-term and long-term impacts of X on Y, and also a method to measure deviations from the mean (Best 2008).

The particular form of error-correction model utilized in this estimation is based on Blackburne and Frank (2007).The basic idea behind the error-correction model is that the error term is corrected for by utilizing error terms from the past. This approach was proposed by Pesaran, Shin and Smith (1997, 1999) in (Blackburne and Frank 2007). Martinez–Zarzoso and Bengochea-Morancho (2004) provide techniques to estimate non-stationary dynamic panels and have found applications in the Environmental Kuznets Curve analysis (Blackburne and Frank 2007).

These authors assume that there exists an Autoregressive Distributed Lag (ARDL) specification represented by the following equation, II.3:

(II.3) $$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{it-j} + \sum_{j=0}^{q} \delta_{ij}^{'} x_{i,t-j} + \mu_i + \varepsilon_{it}.$$

Where the groups are i=1,2……..N,

t=1…………T is the number of periods,

X_{ij} is the $k \times 1$ vector of explanatory variables,

δ_{ij} are the $k \times 1$ coefficient vectors,

λ_{ij} are scalars and,

μ_j is the group specific effect, and

ε_{it} are the error terms (Blackburne and Frank 2007).

This model is then respecified as an error-correction model by using the following equation, II.4:

(II.4) $$\Delta y_{it} = \Phi_i(y_{i,t-1} - \theta_i' x_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{i,t-1} + \sum_{j=1}^{q-1} \delta_{ij}' \Delta x_{i,t-j} + \mu_i + \varepsilon_{it}.$$

Equation 11.4 is a specific instance of general error correction form represented by equation II.2.

There has been widespread use of these mean group (MG) and pooled mean group (PMG) models to time-series cross-section data in the recent past. Evidence of a long-run relationship is provided if Φ_I is significant and negative. The term θ_i' is of interest since it represents the long-run relationship between the variables. Three methods of estimation can be used to estimate the above model (Blackburne and Frank 2007): these are the fixed effects estimation method, the pooled mean group estimation method and the mean group method.

For this analysis, the pooled mean group estimation method is utilized. In the fixed effects estimation approach only the intercepts are allowed to vary across groups. However, if the slope coefficients are not identical, the fixed effects estimator could lead to misleading results. The mean group estimation on the other hand allows both intercepts and slopes, and error variances to vary across groups.

The pooled mean group estimation method is a compromise between the fixed effects estimator and the mean group estimator. This method combines both pooling and averaging; it allows the short-run coefficients and error variances to vary across groups, but the long-run coefficients are held to be equal across groups. The PMG method utilizes the maximum likelihood estimation method to estimate the coefficients (Blackburne and Frank 2007). The PMG model is the only method that is used in this analysis. Equation II.9 is nonlinear in parameters; the maximum likelihood is considered to be the most appropriate method to estimate the model (McCarl et al. 2009).

Results

Tables II. 9 and II.10 present the results of the long-run and short-run estimates of the error-correction model, respectively. The focus of the analysis in this chapter is to examine the effect of increases in yields of different crops, rice, wheat and maize (RY, WY, MY in the long run, and DRY, DWY and DMY in the short run), on land area in agriculture. The long-run coefficients (table II.10.) of rice and wheat yields are negative and significant for the combined and Asian specifications. Maize yield (MY) is found to be negative and significant in the case of the Latin American specification. Maize yield has a negative effect on expansion of agricultural land use in the short run.

The income variables per capita GDP, per capita GDP squared and percentage change in GDP (PGDP, $PGDP^2$, PPGDP**)** are also generally found to be respectively negatively and positively significant, for the combined and Asian specifications; in the case of the Latin American specification (table II.9.), the effect of PGDP is positive. These variables are associated with the Environmental Kuznets Curve (EKC).

The measure for population growth (PPON) is found to positive and significant in the long run for the combined and Asian specifications this result is as expected based on previous theoretical and empirical literature (Barbier 2001, Cropper and Griffiths 1994). The sign of population growth is negative for the combined model.

The structural variables are arable land per person (ARPP) and percentage of land area under permanent crops (CRPL). ARPP when significant is positive for the Asian and combined specifications. The coefficient for CRPL surprisingly is found to be negative in the case of the Latin American specification. In the short run (table II.10), the coefficient of arable land per person (DARPP) is found to be positive and significant across all specifications.

The trade variables do not generally appear to be significant either in the short run or the long run except in the case of wheat trade in the short run (DWHTR), which is positive and significant in the case of Latin American specification. The sign is as expected.

Table II.9. Estimates from the Error Correction Specification (Long-Run Relationship)

	Combined	Latin America	Asia
RY	-1.78E-07***	-3.95E-08	-2.20E-07***
	(0.00)	(0.49)	(0.00)
WY	-1.20E-07*	5.80E-08	-1.65E-07**
	(0.06)	(0.37)	(0.01)
MY	7.73E-08*	-1.49E-07***	1.27E-07**
	(0.08)	(0.00)	(0.01)
ARPP	0.045398***	0.003511	0.049385***
	(0.00)	(0.73)	(0.00)
CRPL	0.001094	-0.01491***	0.002408***
	(0.24)	(0.00)	(0.02)
PGDP	-1.04E-06***	1.61E-06***	-8.87E-07***
	(0.00)	(0.00)	(0.00)
$PGDP^2$	3.94E-11	-7.96E-11	4.90E-11
	(0.20)	(0.70)	(0.13)
PPGDP	0.000468***	-0.00022	0.000405**
	(0.00)	(0.81)	(0.02)
RITR	2.49E-05	-4.1E-05	-7.1E-05
	(0.86)	(0.56)	(0.62)
WHTR	0.000185	0.000371*	-0.00034
	(0.82)	(0.07)	(0.70)
MATR	-7E-05	-0.00018	-0.00161
	(0.93)	(0.84)	(0.21)
PPON	0.007287***	-0.0007	0.008812***
	(0.00)	(0.28)	(0.00)
Likelihood	2500.535	1468.638	1061.49
Sample size	641	411	230

Notes: RY- Rice yield per hectare in Hg; WY- Wheat yield per hectare in Hg; WY- Wheat yield per hectare in Hg; MY- Maize yield per hectare in Hg; ARPP- Arable land (hectares per person; CRPL - Permanent cropland (% of land area); PGDP-GDP per capita (constant 2000 US$) (centered) data; $PGDP^2$ GDP per capita (constant 2000 US $) squared; PPGDP- GDP per capita growth (annual %); PPON- Annual percentage change in population; RITR- Rice export value US$ divided by income; WHTR- Wheat export value US$ divided by income; MHTR- Maize export value US$ divided by income ***- significant at the one percent level **- significant at the five percent level
*- significant at the ten percent level. The values in parentheses, in the above table II.9., are p values.

Table II.10. Short Run Coefficients from the Error Correction Models (Short-Run Relationship)

	Combined	Latin America	Asia
ec	-0.74167***	-0.71345***	-0.94889***
	(0.00)	(0.00)	(0.00)
DRY	9.19E-09	7.32E-10	1.78E-08
	(0.96)	(0.998)	(0.89)
DWY	4.11E-07	4.80E-07	-4.30E-08
	(0.56)	(0.63)	(0.76)
DMY	-9.07E-07**	-1.24E-06*	-2.61E-07***
	(0.03)	(0.06)	(0.00)
DARPP	2.943657***	0.901428**	6.606396**
	(0.00)	(0.01)	(0.01)
DCRPL	0.001315	-0.06981	0.024915***
	(0.98)	(0.41)	(0.00)
DPGDP	-7.7E-05**	-1.1E-05	-0.00016**
	(0.02)	(0.72)	(0.01)
DPGDPS	-3.20E-08	5.33E-08	-2.24E-07
	(0.74)	(0.12)	(0.56)
DPPGDP	-0.00011	-2.6E-05	4.96E-05
	(0.62)	(0.94)	(0.53)
DRITR	0.00349	0.00567	-0.00052
	(0.29)	(0.23)	(0.17)
DWHTR	-0.15474	-1.01144	0.519285
	(0.83)	(0.50)	(0.63)
DMATR	0.002403	0.00705	-0.01447
	(0.83)	(0.62)	(0.13)
DPPON	-0.0357	-0.02379	0.00113
	(0.21)	(0.42)	(0.39)

Notes ec-error correction term DRY- Short run rice yield per hectare in Hg; DWY- Short run wheat yield per hectare in Hg; DMY- Short run maize yield per hectare in Hg; DARPP- Short run Arable land (hectares per person; DCRPL- Short run Permanent cropland (% of land area); DPGDP- Short run GDP per capita(constant 2000 US$) (centered)data; DPGDPS- Short run per capita (constant 2000 US $) squared; DPPGDP- Short run GDP per capita growth (annual %); DPPON- Short run Annual percentage change in population; DRITR Short run Rice export value US$ divided by income; DWHTR- Short run Wheat export value US$ divided by income; DMHTR- Short run Maize export value US$ divided by income.

Discussion of Empirical Support for Each Specific Hypothesis

Angelsen and Kaimowitz's intensive versus extensive land use hypothesis

Table II.11. presents results that can be used to test if there is evidence that intensive land use has a lower impact on rate of agricultural land expansion than extensive land use. We test whether the coefficients of rice yield, a relatively more labor-intensive crop, are lower than those of wheat and maize yield, relatively less labor-intensive crops. The motivation for this hypothesis is basically derived from the comparison of the darker section (results associated with the intensive sector) with the lighter section (results associated with the extensive section) in table II.2. The numbers in table II.11 represent the p-values associated with each of the null-hypothesis tests. The tests employed to compare the differences between coefficients are Wald tests.

Table II.11. Test of Angelsen and Kaimowitz's Intensive and Extensive Land Use Hypothesis

Null Hypothesis tested	Combined	Latin America	Asia
RY≥WY	0.2679	0.1302	0.2996
RY ≥MY	0.0016***	0.9678	0.0002***
RY=MY=WY	0.0079***	0.0072***	0.0004***
MY=WY	0.0301**	0.0050***	0.0024***

Notes: RY- Rice yield per hectare in Hg; WY- Wheat yield per hectare in Hg WY- Wheat yield per hectare in Hg; MY- Maize yield per hectare in Hg.

Table II.11 does not provide much empirical support for Angelsen and Kaimowitz's 2001 hypothesis; the coefficient of rice yield (RY) is found to be significantly lower in value than maize yield (MY) across the combined and Asian models. However, we cannot reject the null hypothesis that the coefficient of rice yield (RY) is greater than that of wheat yield (WY) for any of the specifications. When we test the joint hypothesis that the long run yield coefficients (RY, WY, MY) are all equal, we are able to reject this hypothesis at the 10 % level of significance for all the specifications. Angelsen and Kaimowitz's 2001 land use hypothesis states the coefficient of rice yield should be lower than that of either maize or wheat because rice is a more labor-intensive crop.

Further, we reject the null hypothesis that the coefficient of maize yield (MY) is less than the coefficient of rice yield (RY) for the Latin American specification.

Borlaug hypothesis

Empirical support for the Borlaug hypothesis in this framework is provided when the coefficients of rice yield, wheat yield and maize yield (RY, WY and MY or DRY, DWY and DMY) are found to be negative and significant. This result differs across the crops. Rice and wheat yields support the Borlaug Hypothesis in the case of combined and Latin American models. In the case of the Latin American models, maize yield supports the Borlaug Hypothesis. Barbier (2001) also finds evidence that supports this hypothesis. However in his specification, cereal yields are considered as whole and are not broken into individual crops.

Angelsen and Kaimowitz's open market hypothesis

There is not much empirical support found for Angelsen and Kaimowitz' 2001open market hypothesis. The coefficients of trade for the three crops appear to be insignificant (RITR, MATR, WHTR and DRITR, DMATR and DWHTR) in both the long run as well as the short run in most of the specifications.

Summary and Conclusions

One of the contributions of this study has been its focus on the effect of increases in agricultural production on the rate of expansion of agricultural land. The theoretical basis for this focus is provided by Angelsen and Kaimowitz's (2001) theoretical framework and the Borlaug hypothesis, and their theoretical model has been evaluated empirically. By looking at the yields of several crops, we attempt to capture the differences in the effect of technical progress in the intensive and extensive sectors. The findings of this study indicate that while there is not much empirical support for Angelsen and Kaimowitz's theoretical framework, there is some support for the Borlaug hypothesis.

The analysis in this chapter is most similar to studies that examine empirical evidence for an EKC for deforestation (Bhattarai and Hammig 2001, Culas 2007). However, the focus of those studies is not usually on the impact of agricultural yields, so not much attention has been paid to the Borlaug hypothesis. Barbier's (2001) specification on which the empirical model is based on, finds empirical evidence that supports the Borlaug hypothesis—his coefficient for cereal yield is found to be negative and significant. Our results differ when the effects of cereal yields are decomposed into the different crops. Yield increases in some crops do not appear to be consistent with the Borlaug hypothesis.

Another contribution of this chapter is the integration of theoretical and empirical literature on factors that affect deforestation. We build on Angelsen and Kaimowitz's frameworks to understand the differentiation between immediate and underlying factors that affect specifically deforestation and, more generally, land use. These underlying factors have been controlled in the EKC literature; however, Angelsen and Kaimowitz (1999)'s study differentiates these factors that affect deforestation into immediate and underlying causes. The variables included in the analysis are measures for the underlying causes rather than immediate causes of deforestation. These variables, based on the results of the error-correction model, are found to be significant in the long run rather than in the short run.

The methodological contribution of this literature is to account for the non-stationary nature of the variables by utilizing an error-correction model. There is evidence that the data are cointegrated, on the basis of the Pedroni and Kao test, and, therefore, there is a long run relationship amongst the variables considered. The error-correction model also provides short run and long run effects, and these short run effects could possibly be differentiated into immediate and underlying causes.

CHAPTER III

CAUSALITY IN THE CONTEXT OF THE ENVIRONMENTAL KUZNETS CURVE (EKC)

Introduction

The Environmental Kuznets Curve (EKC) is a hypothesized U-shaped relationship between various estimators of environmental degradation and income per capita (Barbier 1997, Stern 2004). With the availability of pollution data, empirical verifications of the EKC hypothesis have become widespread.

One of the main reasons the EKC hypothesis has generated so much attention is it provides an alternative to Ehrlich and Holdren's (1971) I=PAT (I = impact, P=population, A=Affluence, T=technology) equation, which relates impact (pollution) to population, affluence and technology. This equation forms the basis for both books *The Population Bomb* and *The Club of Rome's Limits to Growth* (Meadows et al. 1972). According to the IPAT equation, population and increasing affluence are the main sources of environmental degradation; the effect of technology is assumed to be neutral. If an EKC-type relationship holds on the other hand, then economic growth might have a positive impact on the environment in the long run. Both the IPAT equation and the EKC hypothesis raise the question, "Does economic development need to slow down to avoid harm to the environment?" (Carson 2010).

There are many theoretical models to explain the dynamics behind the U-shaped curve of an EKC type model. Andreoni and Levinson (2001) explain the micro-foundation of the EKC relationship; according to them, the shape of the curve depends on increasing returns in the technological link between consumption of a desired good and abatement of its undesirable byproduct. This argument supports the theory that technologies could provide a solution to environmental degradation. However, their theory does not support the idea that economic growth is necessary to reduce environmental degradation, since the authors find that technology is not influenced by either growth or institutional structures. Therefore, there is no strong theoretical support for the EKC. Another explanation that has been offered to explain the EKC is increasing returns to the abatement of pollution. Empirical support for the EKC is most commonly provided by regression models, an alternative method that has been proposed to be the generation of decomposition and efficient frontier models. The main empirical insight that can be gained is that pollution does not necessarily increase with economic growth (Andreoni and Levinson 2001).

As noted by Carson (2010), one of the main problems with empirical verifications of the EKC is the difficulty in proving causality. This is a part of the larger problem of not taking into account time-series properties of the data series. Many of the initial empirical specifications are based on reduced-form equations; the drawback of using reduced-form equations is that a certain causality structure is implicit. Very often the econometric properties of a series are ignored; issues that are usually of concern in an empirical study of the EKC are heteroskedasticity, simultaneity, omitted variable bias and cointegration issues (Stern 2004). These issues could all lead to problems in specifying the causal structure between variables. Many of the prominent initial empirical studies of the EKC use panel data, and most of these data are non-stationary; it is then extremely difficult to establish causality since statistically significant coefficients might be a result of spurious correlation rather than a causal relationship between the variables.

The purpose of this chapter is to examine causality within the context of the EKC. Non-stationarity of a time series poses a problem in establishing the direction of causation between the variables, therefore testing for stationarity and cointegration and related topics will be discussed, both generally and within the context of the EKC. Methods employed to establish causality such as the Granger causality and the Directed Acyclical Graph (DAG) approach will be explored, with greater emphasis on the latter approach; the insights gained from these two approaches will be compared and contrasted. Finally, both methods will be employed to test for causality between income per capita and pollution emissions in three well-known data sets.

The next section provides some background on basic time-series concepts. These concepts form the framework for discussing causality within the time-series domain. This discussion primarily draws upon the standard work by Dolado et al. (1990).

Stationarity[9]

Stationarity of a time series refers to the invariance property of the time series. Econometricians are primarily interested in stationary time series since non-stationary series could lead to spurious regressions. According to Yule (1926), if two series are growing over time, they can be correlated even if increments in each of these series are uncorrelated. Specifically, Granger and Newbold (1974) have explored these ideas of non-stationarity and shown that it can lead to spurious regressions (Dolado et al. 1990). Hence, understanding stationarity is a necessary first step in the process of unraveling causal relations in time-series data.

Two working definitions of stationarity are normally employed: first-order (strong stationarity) and second-order (weak stationarity). A time series $\{x_t\}$ is said to be strictly first-order stationary if for any finite sequence of integers $t_1,\ldots,t_k$ and shift h, the distribution of the original and any shifted time series are the same. The time series is said to be weakly stationary or second-order stationary if the mean is constant for all t, and if for any t and k, the covariance between x_t and x_{t+k} only depends on the lag k. In other words, there exists a function such that, for all t and k (Subbarao 2008),

(III.1) $$c(k) = \mathrm{Cov}(x_t, x_{t+k}).$$

For example, a random walk represented by equation III.2 (Perman 2013),

(III.2) $$x_t = x_{t-1} + \varepsilon_t,$$

is an instance of a non-stationary process.

[9] This section provides an overview of standard principles of time-series analysis. The section draws heavily on Dolado et al. (1990).

The expectation and variance of x_t are

(III.3) $$E(x_t) = x_0 \text{ and } var(x_t) = t\sigma^2.$$

Variance is dependent on time, meaning that the series does not satisfy the invariance property required of stationary series. An autoregressive representation of a time series is represented by equation III.4.

(III.4) $$x_t = c + \sum_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t.$$

A test for the presence of unit roots for an autoregressive representation of a time series is a test for stationarity. The Dickey Fuller test is based on this principle. Other tests employed include the Augmented Dickey Fuller test and the Phillips Pherron test (Dolado et al. 1990).

The Dickey Fuller (DF) statistic is used to test if a pure autoregressive AR (1) process has a unit root. Consider the following time series: where ε_t is white noise, t is a time trend and the initial value x_0 is assumed to be known. Assuming without loss of generality that $x_0 = 0$, the data generating process for x_t can be written as

(III.5) $$x_t = \beta_0 + \beta_1 t + \rho x_{t-1} + \varepsilon_t.$$

The test for stationarity is testing the null hypothesis of non stationarity $H_0: \rho = 1$ versus the alternate hypothesis of stationarity $H_1: \rho < 1$,

(III.6) $$\Delta x_t = \beta_0 + \beta_1 t + \Upsilon x_{t-1} + \varepsilon_t,$$

where $H_0: \rho = 1$ is equivalent to $H_0: \Upsilon = 0$ since $\Upsilon = \rho - 1$.The test is implemented through the usual t-statistic of γ (Dolado et al. 1990).

For the Dickey Fuller test, it is assumed that the data generating process was an AR (1) process. However, in the case of the Augmented Dickey Fuller (ADF) statistic we assume that we have an AR (p) process, which is denoted by equation III.7.

(III.7) $$\Delta x_t = \beta_0 + \beta_1 t + \Upsilon_1 x_{t-1} + \sum_{i=1}^{p-1} \Upsilon_{2i}\, \Delta x_{t-i} + \varepsilon_t.$$

An alternative approach based upon the DF procedure is presented by Phillips (1987) and Perron and Phillips (1987). The ADF statistics are based upon the assumption that the disturbance term ε_t is identically and independently distributed; they suggest amending these statistics to allow for weak dependence and heterogeneity in ε_t. Under such general conditions, a wide class of data-generating processes can exist for ε_t; most order Autoregressive Moving Average Process (ARIMA) models are allowed (Dolado et al. 1990).

There are many studies that implement the augmented Dickey Fuller test in the context of the EKC (Soytas et al. 2007, Ang 2007). These studies are usually confined to a single country; most of these studies find that income and other variables normally included in an EKC analysis are non-stationary.

The above tests have also been modified for panel data in EKC studies. Two prominent studies in this area are Perman and Stern (2003) and Dinda and Coondoo (2006). They both use panel versions of the augmented Dickey Fuller test. Perman and Stern (2003) concentrate on sulfur dioxide emissions and find that income and sulfur dioxide emissions are both non-stationary. The focus of Dinda and Coondoo's (2006) work is on the relationship between carbon dioxide emissions and income. They also find the income and carbon emissions series are non-stationary.

The Problems with Non-Stationarity

The results of classical econometric theory are based on the assumption of stationarity. Hence, the standard techniques are no longer valid when the data are non-stationary.

In the specific context of the EKC, non-stationarity of a data series means that a regression analysis could find that there is a relationship between income and pollution emissions when there is in fact none. Perman and Stern (2003), in their cross-sectional panel study of countries across the world, found that both sulfur emissions and income show stochastic trends. How this arises is discussed below. Consider, for example, a regression of income on emissions and we get the result in equation III.8,

$$\text{(III.8)} \qquad \text{Log}\ (\text{emissions}_t) = \underset{(2.05)}{12.35} \ \underset{(6.05)}{-0.095}\ \text{log percapita income at time}_t) + u_t \qquad R^2 = 0.68$$

where the numbers in parentheses are the associated t values, both of which state that the coefficients are significant at the five percent level.

The above model might look plausible. However, the regression is spurious if the residuals of the regression, u_t, are not stationary (Nielsen 2005). When this is true, the results associated with the ordinary least squares (OLS) regression are no longer reliable or valid and could lead to an erroneous conclusion that per capita income has an impact on pollution emissions.

An Integrated Series

Integration is closely related to the concept of stationarity; an integrated series is a non-stationary series that can be transformed into a stationary series by differencing. Box and Jenkins (1970) proved that there exists a stationary transformation of this class of non-stationary series that is achieved by successive differentiation. The order of integration refers to the number of differences that need to be applied to a time series before it becomes stationary.

To avoid finding spurious correlations, an integrated series needs to be differenced to make it stationary. Many of the data series in the EKC literature are integrated of order one; therefore, first differencing the data yields a stationary series. Taking logs and first differencing the data is the transformation that is normally applied. Perman and Stern (2003) found in their study that the income and sulfur dioxide variables are integrated of order one. Other studies have found this level of integration for income and other variables.

Cointegration

Existence of a cointegrating relationship ensures that there is Granger causality in at least in one direction; it indicates a long run equilibrium between two series that is supported by economic theory. Cointegration between pollution emissions and income provides evidence of a causal relationship.

Even when a pair of time series is not stationary, sometimes a linear combination of them is stationary. When this is true, the pair of series is said to be cointegrated. If two time series, x_t and y_t, are cointegrated, then one series causes the other; moreover, any pair of cointegrated series will have an error-correction model representation (Johansen and Juselius 1990). The error-correction form is represented by equation III.9,

(III.9) $Dx_t = \sum_{i=1}^{k-1} \Gamma_i \, Dx_{t-1} + \Pi Y_{t-1} + \varepsilon_t$ (Haigh and Bessler 2004),

where D represents the first difference operator and ε_t is the random "disturbance" term.

Further, if the two series, y_t and x_t, have the same order of integration, in most cases any linear combination of these two series will also have the same order of integration. However, if there is a linear combination of the series that is integrated of a lower order, then the pair of series is cointegrated at the lower order of the linear combination. Economic theory then suggests the long-run relationship between the two time series, y_t and x_t, can be represented by equation III.10.

(III.10) $y_t = \alpha - \beta x_t + z_{t-1}$.

Note that the term z_{t-1} in equation III.10 represents the difference between the two series in the previous period (Dolado et al. 1990). In the context of the EKC, cointegration tests have often failed to reject the hypothesis of no cointegration. Perman and Stern (2003) use cointegration analysis to test for a long-run relationship between sulfur dioxide emissions and per capita income across 74 countries and for a time period of 31 years. They find that the data contain a linear trend and are, therefore, non-stationary. To identify a causal EKC relationship, therefore, they need evidence that the income and emissions cointegrate. The individual regressions they carry out provide no evidence of such a relationship. Therefore, they do not find an EKC relationship for sulfur emissions. Stern (2004) provides examples of other studies which also find no evidence of cointegration. For example, Day and Grafton (2003) test for cointegration, using a Canadian time series; they find they cannot reject the null hypothesis of no cointegration (Stern 2004).

Normal cointegration tests assume that the order of integration between variables is an integer. However, fractional integration relaxes this assumption and allows both the order of integration as well as the order of cointegration to be a fraction. Initial studies using traditional panel cointegration tests showed that the carbon dioxide emissions series and the income series were not cointegrated. Therefore, a long-run causality relationship could not be established between the variables. However, when Galeotti et al. (2009) carried out a fractional cointegration study, they found that carbon dioxide emissions and income were cointegrated in the long run.

Another approach, often used within the EKC literature to test for cointegration between the variables is the autoregressive distributed lag model (ARDL), represented by equation III.11.

(III.11) $$y_t = \beta_0 + \beta_1 y_{t-1} \ldots + \beta_k y_{t-p} + a_0 x_t + a_1 x_{t-1} + \cdots \ldots\ldots + a_q x_{t-q} + \varepsilon_t,$$

where ε_t is a random "disturbance" term. A bounds test is used to test for the presence of a long-run equilibrium between the variables. This approach has an advantage over others; it can be employed when there is a mixture of both stationary and non-stationary variables (Giles 2012). It is frequently used within the pollution context to study the relationship between carbon dioxide emissions and GDP per capita. These studies generally find evidence of a long-run relationship between carbon dioxide emissions and GDP per capita. Examples include Martinez-Zarzoso and Bengochea-Morancho (2004), Soytas et al. (2007) and Iwata et al. (2010).

Causality

The definition of causality provided by Hume is the basis of many of the empirical tests for causality. Hume defines causality as follows:

> "We may define a cause to be an object, followed by another, and where all the objects similar to the first are followed by objects similar to the second. Or in other words where, if the first object has not been, the second never had existed" (Hume 1748, Sect. VII, part II) in Kwon and Bessler (2011).

The above statement provides two definitions of causality. These two definitions might be represented by the two probability statements, III.12 and III.13:

(III.12) $P(A|B) > P(A)$, and

(III.13) $P(A|B^C) = 0$.

The second statement is the basis for the counterfactual or the manipulative concept of causality. Consider a situation in which event A is rain and event B is lightning. Event B^c refers to the situation where there is no lightning. We can see that the presence of lightning might well increase the chances of rain; but there can be rain without lightning. Therefore, the second statement, III.13, would not be valid. However, if the first statement is used to define causality, the conclusion would be that lightning causes rain. Consider another situation, where event A is again rain and event B is the appearance of clouds. Now both statements are satisfied, and we would conclude that clouds cause rain. Probability statement III.13 is, therefore, a stronger definition of causality. Granger causality is primarily based on the first statement and provides a test of probabilistic causality for time-series data.

Holland (1986) has defined an empirical test of causality, based on the second statement or the manipulative concept of causality. However, Holland's definition is for experimental rather than observational data (Kwon and Bessler 2011). A method that attempts to provide empirical tests for causation for both non-temporal and non-experimental data is the graphical causal approach; this method is elaborated further following the discussion on Granger causality. Alternative approaches to causality within economics might be represented by table III.1. These approaches, on one hand, may either emphasize structure or process or, on the other hand, may rely on either a priori identifying assumptions or seek to infer causes from the data (Hoover 2008).

Regressions, often used to provide empirical support for the EKC hypothesis, usually employ the a priori approach. Granger causality, on the other hand, is a process inferential approach. It is based on empirical information, and there is no direct reference to background theory. The DAG theory does not fit solely into one of the cells given above; it is an inferential approach which straddles both cells on the inferential row in table III.1 (Hoover 2008).

Table III.1. Approaches to Modeling Causality in Economics

	Structural	Process
Apriori	Cowles Commission	Zellner(1979)
	Koopmans (1950)	
	Hood and Koopmans (1953)	
Inferential	Simon (1953)	Granger (1969)
	Hoover (1990, 2001)	Vector auto regressions
	Ferraro experiments	Sims (1980)

Source: Figure 1 Kevin Hoover (2008) Pg. 3 The New Palgrave Dictionary of Economics Edited by Steven N. Durlauf and Lawrence E. Blume reproduced with permission of Palgrave Macmillan. This material may not be copied or reproduced without permission from Palgrave Macmillan

Granger Causality

Assume we have three time series x_t , y_t and w_t, and want to establish the causal relationship between the series x_t and y_t given w_t .We first attempt to forecast y_{t+1} using $x_{t,}$ y_t controlling for w_t. We then consider all three variables, x_t, w_t and y_t, in predicting x_{t+1}. If the second forecast is more successful than the first forecast, then we can conclude that y contains some information not contained in the past values of x and w, which helps in forecasting x_{t+1}. w_t does not have to be a single variable; it could be the vector of all the explanatory variables or controls. The accuracy of the assertion that y_t causes x_t, is dependent on the size and stringency of w_t.

Granger causality might also be defined as:

(III.14) x_t Granger causes y_{t+1} If P (y_{t+1}| all information dated t and earlier) $\neq$ P(y_{t+1} | all information dated t and earlier omitting information about x) (Hoover 2008).

The test for Granger causality uses the vector autoregression (VAR) model. The VAR model is the generalization of the autoregression model. It is represented by equation III .15:

(III.15) $x_t = A_1 x_{t-1} + A_2 x_{t-2} + \ldots\ldots\ldots A_p x_{t-p} + \varepsilon_t$.

To test for Granger causality we consider the bivariate VAR in equation III.16,

(III.16) $\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \sum_{i=1}^{p} \begin{bmatrix} \alpha_{11i} & \alpha_{12i} \\ \alpha_{21i} & \alpha_{22i} \end{bmatrix} \begin{pmatrix} x_{t-i} \\ y_{t-i} \end{pmatrix}$.

The variable x_t is said to not Granger cause y_t if and only if α_{12i} =0, $i = 1,2 \ldots p$ this result is said to hold for both integrated as well as stationary processes (Luetkepohl 2011).

According to Engle and Granger (1987), if a pair of series is cointegrated, it can be said there is a causal relation or Granger causality in at least one direction. However, if there is a Granger causal relationship, it does not imply that the series are cointegrated.

While the Granger causality test has been utilized to understand the nature of causality between variables, the results from this approach are often questioned. The Granger causality approach is based on the ability of one variable to predict the other variable. The second definition of causality is based on manipulation. Variable y causes variable x only if values of x can be changed by changing values of y. One of the drawbacks of using Granger causality is that it does not fully address causality from the manipulation perspective (Kwon and Bessler 2011).

Structural causality neither implies Granger causality nor is implied by Granger causality (Hoover 2008); it is also insufficient to solve the identification problem and is finally sensitive to the information problem (Kwon and Bessler 2011). Previous studies have used Granger causality to determine the direction of causation between income and pollution emissions (e.g., Perman and Stern 2003). Income is often found to be non-stationary or integrated. For there to be a causal relationship, the variables considered must be either stationary or cointegrated. There is not too much statistical evidence supporting causality in EKC-type relationships. It is not possible to use the results of the Granger causality test to determine if a long-run equilibrium between income and pollution emissions exists. Therefore, we cannot infer that changes in income lead to changes in pollution emissions (Carson 2010). Coondoo and Dinda (2002) test for Granger causality between carbon dioxide and income at the global level. First, their study reveals that for developed country groups of North America and Western Europe, carbon emissions Granger cause income. Secondly, for the country groups of Central and South America, Oceania and Japan, income Granger causes emissions. Finally, for country groups in Asia and Africa the causality is bi-directional. Income and emission growth rates reinforce each other. As mentioned earlier, no conclusions can be reached about the long-run relationship between income and emissions.

The studies cited so far, Perman and Stern (2003) and Coondoo and Dinda (2002), are panel-level studies. Within the EKC context, Granger causality is frequently employed to study the relationship between carbon dioxide, energy use and emissions for a single region (e.g., Soytas et al. 2007); these studies find that energy use Granger causes emissions. The relationship between energy use and income is tenuous (Soytas et al. 2007). Variations in these studies involve the inclusion of variables that measure the extent of alternative sources of energy, trade and output growth. Iwata et al. (2010) include the consumption of nuclear energy in their study of the causal relationships between energy use, income and emissions in France. They find a unidirectional relationship between nuclear energy and carbon dioxide emissions, providing evidence that nuclear energy plays an important role in reducing carbon dioxide emissions.

Directed Acyclical Graph

An alternative method used to test for causality between variables is the Directed Acyclical Graph (DAG) approach (Pearl 1995). A DAG is a pictorial representation of the causal flow of information between variables. The letters $V_1, V_2 \ldots V_n$ are used to represent the variables included in the model. Lines with arrows represent the direction of causal flow of information between variables. These graphs represent conditional independence as implied by the recursive product decomposition characterized by equation III.17:

(III.17) $$\mathrm{pr}(x_1, x_2 \ldots \ldots \ldots \ldots \ldots . x_n) = \prod_{i=1}^{n} \mathrm{pr}(x_i \,|a_i),$$

where pr is the probability of the variables or vertices of the graph, and pa_i is the realization of some subset of the variables that precedes the variable x_i. According to Pearl (1986), the conditional independence relationships in equation III.17 can be characterized graphically by using the property of D separation. Pearl (1995) defines D separation as follows:

Let X, Y and Z be three disjoint subsets of vertices [variables] in a directed acyclic graph G, and let p be any path between vertex [variable] in X and a vertex [variable] in Y, where by 'path' we mean any succession of edges, regardless of their directions; Z is said to block p if there is a vertex w on p satisfying one of the following: (i) w has converging arrows along p, and w is in Z. Further, Z is said to d- separate X from Y on graph G, written $(X \perp Y|Z)_G$, if and only if Z blocks every path from a vertex [variable] in X to a vertex [variable] in Y in Bessler et al. (2003, page 776).

The connection between directed graphs and the random assignment model of Rubin (1978) and Holland (1986) is shown by Spirtes et al. (1999). This implies that observational data can be represented by a DAG if they satisfy the following three criteria (Haigh and Bessler 2004):

- Causal sufficiency condition: In the DAG there are no omitted variables that cause any two of the included variables in the study.
- The Markovian condition: The causal flows included in the DAG respect a causal Markov condition. Consider variables, x, y and z. If x causes y and y causes z, the underlying probability distribution on x, y and z can be factored as pr(x,y,z) =pr(x)pr(y|x)pr(z|y).
- The faithfulness condition: Any two variables x and y included in the DAG are dependent if and only if there is an edge between x and y (Haigh and Bessler 2004).

Various algorithms can be used to generate the graph. Two algorithms commonly used are: the Peter and Clarke (PC) algorithm and the Greedy Equivalence Search (GES) algorithm.

The PC algorithm begins by forming a completely undirected graph; all the variables are connected by undirected edges. Edges are then removed stepwise between variables on the basis of tests of correlation. The PC algorithm employs the Neyman-Pearson type of statistical tests of partial correlation. It assumes that the variables follow linear Gaussian distributions.

The GES algorithm, on the other hand, is based on the goodness-of-fit scoring approach. This approach first defines the search space that contains all possible causal hypotheses represented by DAGs. It is based on the Bayesian Information Criterion (BIC). A goodness-of-fit measure is then used to choose the causal structure or DAG that best explains the data. One of the drawbacks of this approach is that the number of causal structures rapidly increases when the number of variables N increases.

Both the PC and the GES algorithms are based on the assumption that the residuals are Gaussian. However, in practice very often the residuals are not normal. In these cases, algorithms such as the Linear Non Gaussian Acyclic Model (LiNGAM) and PC LiNGAM are used to generate the graphs. These algorithms are based on the idea that if residuals of a process are not Gaussian then higher order moments can be used to identify the equation (Moneta et al. 2013).

One way of obtaining the residuals used to generate a DAG, is to use a VAR specification to model the data. As mentioned earlier, one of the drawbacks of the

Granger causality approach is its sensitivity to the original choice of explanatory variables. The DAG approach, on the other hand, does not induce the difficulty of deciding on the appropriate set of explanatory variables in the initial search step. Granger causality is associated with the VAR, whereas the DAG approach is associated with the structural vector auto regression (SVAR). Granger causality based on temporal ordering is not the scientific or philosophical foundation for a causal relationship (Kwon and Bessler 2011). The VAR does not provide sufficient information to study causal shocks of variables to economic systems; whereas, the SVAR allows for the recovery of causal relationships between variables. SVAR traces out how economically interpreted random shocks affect the system. If the Markov condition, the faithfulness condition and the causal sufficiency are satisfied, it is often enough to identify the SVAR. Very often these conditions are violated, but the SVAR can also be identified based on weaker conditions; if the residuals are non-Gaussian, alternate methods can be exploited to generate these graphs.

In many disciplines, the DAG technique has been applied to generate the causal flows between variables in observational data. Phenomena in agricultural economics are observed using the lens of experimental data or the lens of observational data. Causal frameworks are specified in experimental settings. However, there are many cases where experimental inquiry, and, therefore, random assignment, is not possible. Observational data, where the causal framework is not so well specified, are used to understand such phenomenon. DAGs can be used to understand the causal relationships between variables observed through the lens of observational data (Bessler 2013). For example, DAGs are used to understand the relationship between prices and key macroeconomic variables (Kwon and Bessler 2011).

Data

In this chapter, evidence for causal relationships between pollution emissions and income is examined utilizing 4 commonly used datasets. Within the EKC context: sulfur, sulfur dioxide and carbon dioxide emissions are the most commonly used pollution indices. In this analysis, greater emphasis is placed on the relationship between sulfur (sulfur and sulfur dioxide) emissions and income, due to the regional nature of sulfur pollution, whereas, carbon dioxide is a global pollutant. The difference in the nature of the two pollutants could have an impact on the causal relationships between variables.

The datasets for sulfur, sulfur dioxide emissions and carbon dioxide emissions have been previously used in Harbaugh et al. (2002)[10], Dijkgraaf and Vollebergh (2005)[11], Vollebergh et al. (2009) and Stern and Common (2001)[12].

The first dataset considered is Harbaugh et al.'s (2002) version of Grossman and Kreuger's (1995) dataset. Harbaugh et al. (2002) clean up and reexamine the evidence for the EKC. Ten years of additional data are added to the original dataset so that the data now extend from 1971 to 1998. The new data are collected from the Aerometric

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[10] Data was obtained from the authors.
[11] Data was obtained from the authors.
[12] Stern (2013) Accessed data on March 12th 2013 from http://www.sterndavidi.com/datasite.html.

Information Retrieval System (AIRS) and the World Health Organization. The original datasets are based on ambient pollution data, first collected by the Global Environmental Monitoring system (GEMS) (Harbaugh et al. 2002). Sulfur dioxide emissions are measured in micrograms per cubic meter (μg/m^3). The sources for the GDP data are the Penn World tables. Real per capita income is measured in 1000's of 1985 US dollars. The summary statistics for these data are presented in table III.2. Very preliminary analysis is carried out on these data. The data are unbalanced and there are very few observations within each panel. Annual data are collected for certain cities.

Table III.2. Summary Statistics for Harbaugh's Data

	Sulfur dioxide	GDP
Mean	83.661	8.343
Standard Deviation	102.276	5.522
Minimum	0.782	0.765
Maximum	1159.854	18.095

The second dataset, which we will refer to as the DV dataset, is the basis for EKC analyses in more recent literature. The data on carbon dioxide emissions is used in Dijkgraaf and Vollebergh (2005), and the combined dataset is used in Vollebergh et al. (2009). Annual carbon dioxide and sulfur dioxide emissions are reported from 1960 to 2000. Only Organisation for Economic Co-operation and Development (OECD) countries are included. The original data sources are OECD (2000) and International

Energy Agency IEA/OECD (1991). The authors calculate carbon dioxide emissions using data on total energy supply. The DV data are corrected for non-energy use of fuels such as chemical feed stocks. Fuels incorporated in calculating the carbon emissions include coal, other solid fuels, crude oil petroleum products and natural gas (Dijkgraaf and Vollebergh 2005). Sulfur dioxide emissions are calculated on the basis of estimated sulfur content and sulfur retention or removal of waste streams (Vollebergh et al. 2009).

Descriptive statistics for these variables are presented in table III.3. Twenty-four countries are included in this analysis: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States of America. Summary statistics for these data are presented in table III.3. Forty-one observations on carbon dioxide, sulfur dioxide emissions and per capita GDP are available for each country. Figure III.1[13] is a representation of the relationship between per capita GDP and per capita carbon dioxide emissions for six selected countries; per capita carbon dioxide emissions are measured in millions of metric tons, whereas sulfur dioxide emissions are measured in metric tonnes. Per capita GDP is measured in 1990 US dollars. The source for the data on population and GDP is also the OECD (Dijkgraaf and Vollebergh 2005).

[13] Luxembourg is not included in the analysis since it is an outlier.

Table III.3. Summary Statistics (Dijkgraaf and Vollebergh 2005) and (Vollebergh et al. 2009)

	GDP	Carbon dioxide	Sulfur dioxide
Mean	13172.33	2605.501	28.672
Standard Deviation	4992.064	1801.395	24.044
Minimum	2770.521	166.541	1.253
Maximum	33634.744	12333.352	154.291

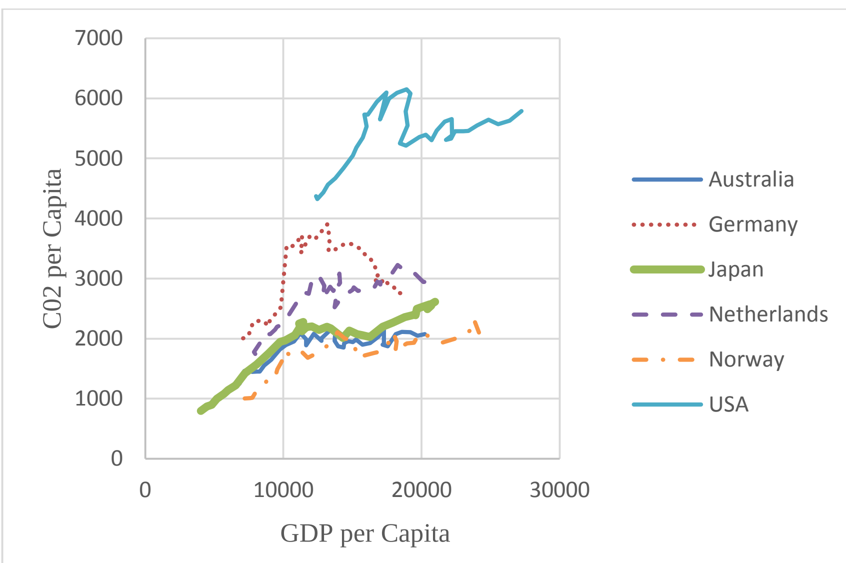


Figure III.1. The Relationship between Carbon Dioxide Emissions and Income for Selected Countries

Figure III.2 presents the relationship between sulfur dioxide emissions and GDP for five representative countries in the DV dataset. USA and Canada are outliers with much higher levels of SO_2 per capita; therefore, they are not included in this representation as it would be difficult to appreciate the general trend in emissions among other countries.

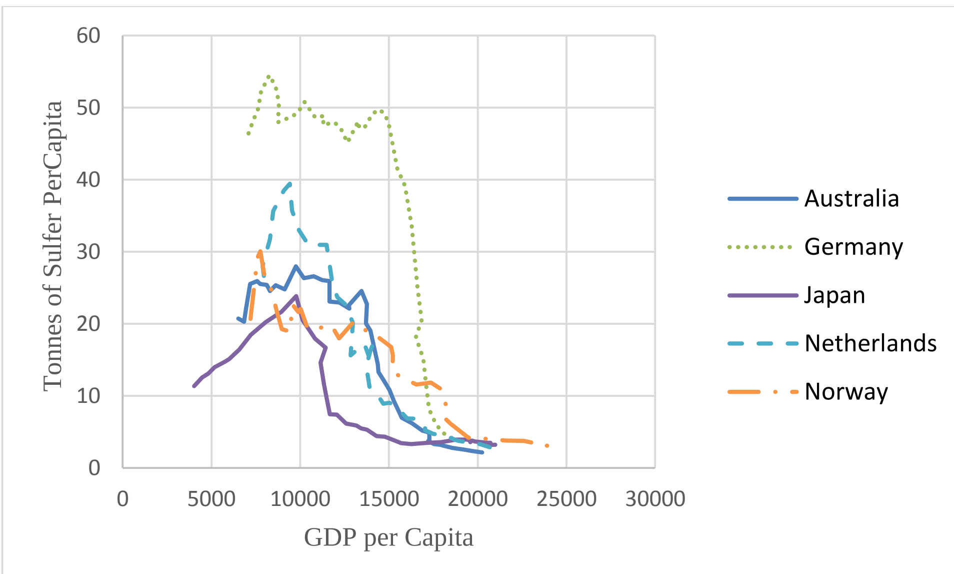


Figure III.2. Sulfur Dioxide Emissions and Income for Selected Countries

The third dataset (SC) was developed by Stern and Common (2001) to estimate an EKC for sulfur emissions for both developing and developed countries. The source of their sulfur emissions is based on a report by A.S.L. & Associates for the US Department of Energy. Total sulfur emissions include emissions from burning hard coal, brown coal and petroleum and sulfur emissions from mining smelting activity for most countries across the world. The original A.S.L. & Associates dataset contains annual observations from 1850 to 1990. A complete list of the 74 countries included in the SC dataset is provided in appendix A.IV... Data for twelve selected countries (both OECD and non-OECD) are presented in figure III.3. Stern and Common (2001) use annual data from 1960 to 1990. The units of measurement for sulfur emissions are tonnes per capita. GDP is measured in per capita US$ of 1990 PPP. The sources for GDP data are the Penn World tables. Summary Statistics are presented in table III.4.

Table III.4. Summary Statistics (Stern and Common 2001)

	GDP	Sulfur
Mean	5359.908	0.022
Standard Error	6244.168	0.037
Minimum	303.000	8.85E-07
Maximum	80830.800	0.466

Methodology

This section discusses the steps involved in revealing the causal relationships between pollution emissions and income. In the first step, pollution and income variables are tested for stationarity. In the second step, the panel VAR model is applied to the data and Granger causality tests are carried out. In the third step, the residuals of the VAR model are checked for normality. On the basis of these results, in the fourth step, the appropriate causality tests and DAG algorithms are selected. In the fifth and final step, the results of these causality tests are discussed.

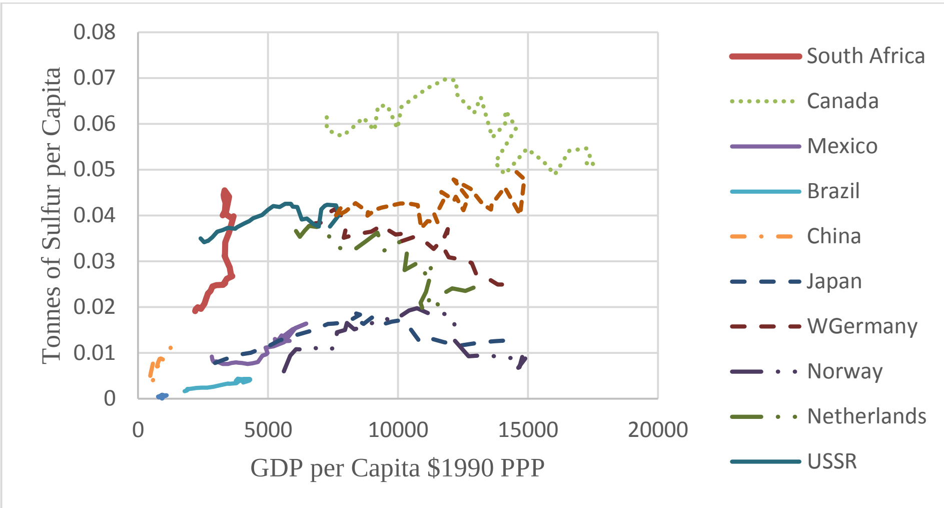


Figure III.3. Sulfur Emissions and GDP for Selected Developing and Developed Countries

Stationarity tests

Three commonly used tests, Lev Lin Chu (LLC), Im Pearson and Shin (IPS) and Breitung, are carried out to examine the stationarity of variables. Greater details on these tests are provided in appendix A.II.. Per capita sulfur dioxide emissions data are found to be non-stationary by all three stationarity tests. This result is common to both DV's and SC's datasets. However, the results of the LLC and the IPS tests indicate that the hypothesis of non-stationarity can be rejected for carbon dioxide emissions, per capita GDP and per capita GDP squared. This result is, however, not supported by the

Breitung tests; therefore, it is concluded that all the variables considered in this analysis are non-stationary. The lag lengths for the stationarity tests are chosen on the basis of the Bayesian Information Criterion (BIC). The values in tables III.5, III..5 are p values associated with the null hypothesis of non-stationarity.

Table III.5. Stationarity Tests for DV's Data. (H0: At Least One of the Panels Contain Unit Roots).[14]

	LLC (p values)	Breitung (p values)	IPS (p values)
Soiln	1.000	1.000	1.000
Coiln	0.000	0.993	0.000
GDPiln	0.000	1.000	0.000
GDPilnsq	0.000	1.000	0.032

Table III.6.: Stationarity Tests for Stern and Common's (2001) Data. (H0: At Least One of the Panels Contain Unit Roots).

	LLC (p values)	Breitung (p values)	IPS (p values)
Soiln	0.005	0.547	0.891
GDPiln	0.000	1.000	0.898
GDPilnsq	0.000	1.000	0.992

[14] The entire sample is considered while conducting the stationarity tests. Though, Luxembourg is dropped, while considering the DV dataset. The outcomes of the stationarity tests still remain the same when Luxembourg is not included

In addition to being non-stationary, the data might also contain fixed effects; therefore, the Helmert transformation is applied to the data to remove the fixed effects. The Helmart transformation is a forward mean differencing procedure. After this transformation, the data are first differenced to remove trend effects. The three stationarity tests are once again carried out on the transformed data. The null hypothesis of non-stationarity is rejected for all three variables, by all three tests. This result holds true for both DV's and SC's datasets. These results are presented in tables III.7 and III.8.

Table III.7. Stationarity Tests for DV's (2001) Data (First differenced and Helmart Transformed). (H0: At Least One of the Panels Contain Unit Roots).

	LLC (p values)	Breitung (p values)	IPS (p values)
dCoiln	0.000	0.000	0.000
dSoiln	0.000	0.000	0.000
dGDPiln	0.000	0.000	0.000
dGDPilnsq	0.000	0.007	0.000

Table III.8. Stationarity Tests for Stern and Common's (2001) data (First Differenced and Helmart Transformed). (H0: At Least one of the Panels Contain Unit Roots).

	LLC (p values)	Breitung (p values)	IPS (p values)
dSoiln	0.000	0.000	0.000
dGDPiln	0.000	0.000	0.000
dGDPilnsq	0.000	0.000	0.000

Panel VAR

The VAR structure treats all variables considered in the model as endogenous and interdependent and is, therefore, the appropriate method to employ when examining the causal structure between variables. The panel VAR structure is similar to the VAR structure discussed earlier; however, another dimension is added. Equation III.18 is a representation of a panel VAR model. The panel VAR technique combines the traditional VAR approach and the panel data approach. All the variables considered are endogenous like the traditional VAR approach; however, it also allows for unobserved individual heterogeneity like the panel data approach (Klien 2010).

(III.18) $$Y_{it} = A_0 + \sum_{s=1}^{n} A_p Y_{i,t-p} + f_i + e_{it},$$

where, Y_{it} is the vector of endogenous variables for region i in the time t, which in this analysis would be either per capita carbon dioxide or per capita sulfur emissions or per capita GDP for country i in year t. The term f_i captures country-specific fixed effects.

This methodology is used to generate the relationship between pollution emissions and income for DV's and SC's datasets. It is not used for Harbaugh et al.'s (2002) dataset due to the unbalanced nature of the data. The results are generated for sulfur dioxide and carbon dioxide emissions and are presented in table III.9. The results for DV's data are generated without Luxembourg data on carbon dioxide emissions. Similarly, the panel VARs for DV's data on sulfur dioxide emissions are also generated without US and Iceland data. These data are outliers and could significantly affect the specification of the model.

The choice of the appropriate lag length is based on the Schwarz Bayesian criteria (SBC)[15]. The optimal lag lengths for DV's datasets on carbon dioxide and sulfur dioxide are three and one, respectively; however, the optimal lag length for SC's dataset is 4. The results of the panel VAR model are presented in table III.9. Before estimating the panel VAR, as mentioned earlier, the Helmert transformation is applied to control for endogenity created by the correlation between the lags and the explanatory variable. After this, data are first differenced to remove trend effects. The first-differencing procedure introduces a simultaneity problem because lagged endogenous variables are correlated with the new differenced error term; to account for this problem, the Generalized Method of Moments (GMM) method is used to estimate the model. Impulse response functions are also generated and are presented in appendix A.V.. The impulse response functions describe the reaction of one variable to innovations in another variable; all other variables are held constant (Love and Ziccinio 2006). The panel VAR specifications presented in table III.9 are used to generate residuals:

dlnGDP- first differenced natural log of per capita GDP

dlnCO2- first differenced natural log of per capita carbon dioxide emissions

dlnSO-first differenced natural log of per capita sulfur dioxide or sulfur emissions

[15] At five lags the determinant of the variance-covariance matrix for the residuals for Stern's dataset first increases slightly before decreasing.

Table III.9. Panel VAR Results

CO_2			SO_2				
	DV's data			**DV's data**		**SC's data**	
	dlnGDP	**dlnCO2**		**dlnGDP**	**dlnSO2**	**dlnGDP**	**dln SO2**
Lag1	.378***	.468***	**Lag1**	.478***	.611***	.180***	.308*
dlnGDP	(.047)	(.092)	**dlnGDP**	(.035)	(.222)	(.041)	(.180)
Lag 1	.067***	-.077*	**Lag 1**	-.012*	-.016	.002	.099
dlnCO2	(.018)	(.044)	**dlnSO2**	(.007)	(.095)	(.009)	(.084)
Lag 2	-.017	.020*	**Lag 2**			-.004	.169
dlnGDP	(.050)	(.099)	**dlnSO2**			(.034)	(.135)
Lag 2	-.008	.018*	**Lag 2**			-.002	-.091
dlnCO2	(.018)	(.043)	**dlnSO2**			(.006)	(.079)
Lag 3	.161***	.127*	**Lag 3**	.		.108***	.096
dlnGDP	(.043)	(.086)	**dlnGDP**			(.030)	(.113)
Lag 3	.024	.094**	**Lag 3**			-.011*	-.060
dlnCO2	(.017)	(.038)	**dlnSO**			(.007)	(.042)
			Lag4			.014	-.036
			dLnGDP			(.028)	(.122)
			Lag 4			.008*	-.019
			dlnSO			(.004)	(.027)

Note: ∗∗∗,∗∗, and ∗ represent significance at the 1%, 5% and 10% levels; standard errors are reported in parentheses.

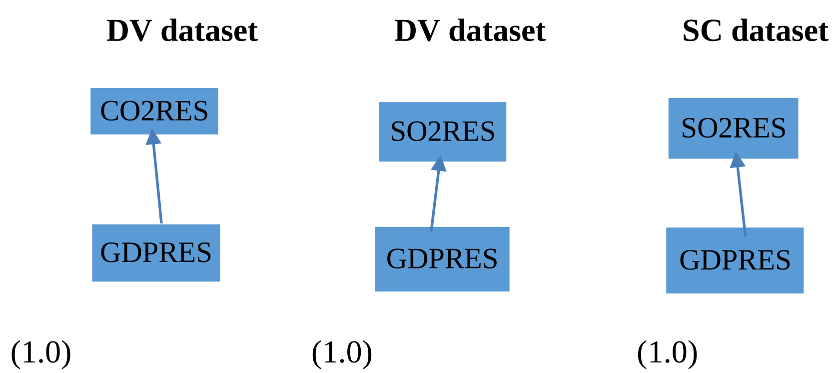
The residuals from the panel VAR are tested for normality using the Skewness and Kurtosis (SK) test. The variables, themselves, are also tested for normality. The results of these tests are presented in appendix A.V... The results of the SK test suggest that the residuals and the variables are not normally distributed. Therefore, causality can be established on the basis of higher order moments (Moneta et al. 2013). The DAG diagrams illustrate the causal relationship between per capita GDP and per capita pollution emission variables.

Directed Acyclical Graphs (DAG)

DAGs are used to convert VARs into Structural VARs (SVARs). While VARs cannot be used to determine causal relationships between variables, SVARs furnish VAR models with structural information, so that one can recover the causal relationships under investigation. The SVAR places additional restrictions on the error matrix compared to the VAR Baum (2013). Theory or information provided by DAGs is used in the SVAR procedure to make assumptions about contemporaneous correlations of the error terms.

When the residuals are not normally distributed, as mentioned earlier, the LiNGAM algorithm is used to generate the DAGs. This algorithm exploits the non-linearity of the residuals; this aids the identification of causal relationships between variables. Though Gaussian data are analytically easier to handle than non-Gaussian data, non-Gaussian data impose a lot more structure, making it easier to identify causal relationships between variables. LiNGAM assumes that the variables are linear and non-Gaussian. The steps involved in this process are as follows: Independent Component Analysis (ICA) is employed to estimate the coefficient matrix. ICA is a technique that is closely related to Principal Component Analysis (PCA). PCA transforms the original space such that the computed latent components are (linearly) uncorrelated. The ICA goes one step further and attempts to minimize all the statistical dependencies between the resulting components (Moneta et al. 2013). The coefficient matrix is then rearranged to obtain a causal order. In the final step, the algorithm prunes the weak coefficients by setting them equal to zero (Ramsay 2013).

The residuals from the PVARs were used to generate DAGs. These figures clearly indicate that the direction of causality between variables is unidirectional; per capita GDP influences per capita emissions in all cases, and these are represented by the directed acyclical graphs generated below. In this context, it means that changing values of income in contemporary time will lead to changes in the value of pollution in contemporary time. This entire process is known as the VARLiNGAM procedure. These diagrams are generated using the computer program TETRAD. The diagrams below show that the data indicate that changing values of GDP in current time will lead to changes in values of pollution in current time. They are a representation of the manipulative approach to causality within the EKC context. This causal relationship is used to inform the DAGs generated to describe the EKC relationship.



Notes: CO2 RES = carbon dioxide residuals from the panel VAR specification; SO2 RES = sulfur dioxide residuals from the panel VAR specification; GDPRES = per capita GDP residuals from the panel VAR specification.

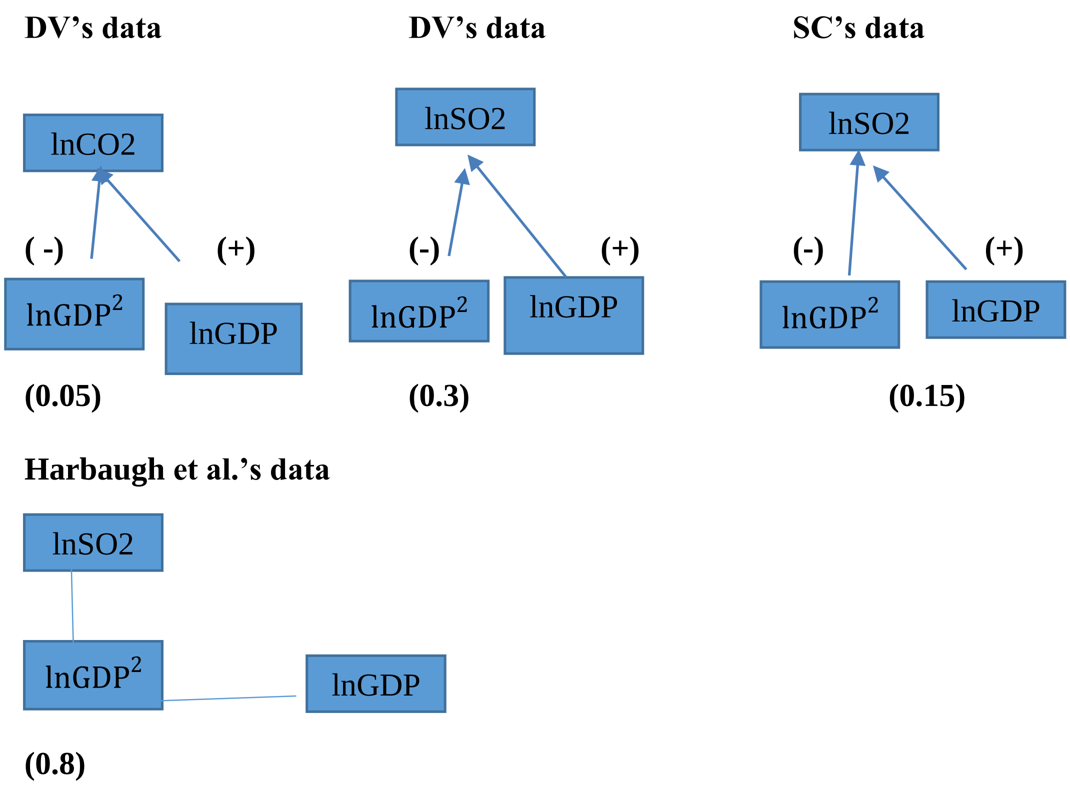
Figure III.4. DAGs Generated Using the LINGAM Algorithm (PVAR Residuals)

The DAGs in figure III.4 can be used to capture an EKC type of relationship. The option of including prior knowledge is employed here; based on the above causality results, the variable, pollution emissions, is chosen as an exogenous variable, whereas, GDP and GDP squared are chosen to be endogenous variables. No such knowledge and restrictions could be used for Harbaugh et al.'s (2002) data. The DAGs that use this prior information are presented in figure III.5 (except Harbaugh's dataset). There is evidence of an EKC relationship for the DV's carbon dioxide dataset at the 5% level of significance. The direction of causation is not apparent as prior information cannot be used for Harbaugh's dataset. These results are generated using the PC[16] algorithm, discussed earlier. The EKC relationship is observed for DV's and SC's datasets at a much higher level of significance. In order to generate an acyclic graph, a restriction is placed such that per capita GDP and per capita GDP squared cannot influence each other. The DAGs provide a representation of causality in contemporaneous time and are based on the manipulative definition of causality versus a predictive definition of causality.

The relationships estimated reveal that there is evidence supporting a U-shaped relationship between the variables considered. The direction of the relationship between variables is based on ordinary least squares (OLS) regression results. The relationship between per capita income and emissions is positive, and the relationship between per

[16] The PC algorithm assumes that variables follow a Gaussian distribution. This assumption is violated. The LiNGAM algorithm is also used to generate these results, however TETRAD does not allow for use of previous knowledge for the LiNGAM algorithm.

capita income and income squared is negative. The direction of causality cannot be determined between per capita GDP and per capita GDP^2; therefore, to generate a DAG, a restriction must be placed on these variables. When unrestricted, an edge is present; this presence suggests that there is a relationship between these variables; however, the direction of causality cannot be directed by the information given. The causal relationship between per capita GDP and per capita GDP^2 can be restricted using previous knowledge.



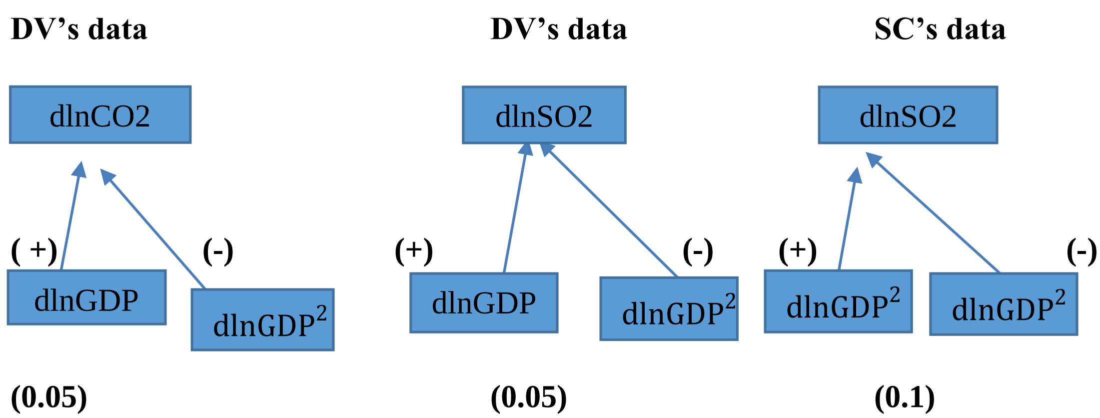
Notes: lnSO2 = natural log of per capita sulfur dioxide emissions; lnCO2 = natural log of per capita carbon dioxide emissions; lnGDP = natural log of per capita GDP; lnGDP^2 = Square of the natural log of per capita GDP.

Figure III.5. DAGs Generated Using the PC Algorithm (Non-Stationary Data)

In that case, all that remains is the EKC relationship between per capita pollution emissions, per capita GDP and per capita GDP^2. Alternate specifications of the DAGs generated within the EKC context are presented below, in figures III.6. and III.7. These DAGs are generated for stationary data.

The levels of significance at which the EKC relationship is said to exist are presented in the parentheses below the DAG's. For the PC algorithms, these are p values, and for the LiNGAM algorithms these are the prune factors. For the DV's carbon dioxide and sulfur dioxide dataset both the PC and LiNGAM algorithms support an EKC relationship at the 0.05 level of significance and 0.7 and 0.98 prune values.

This

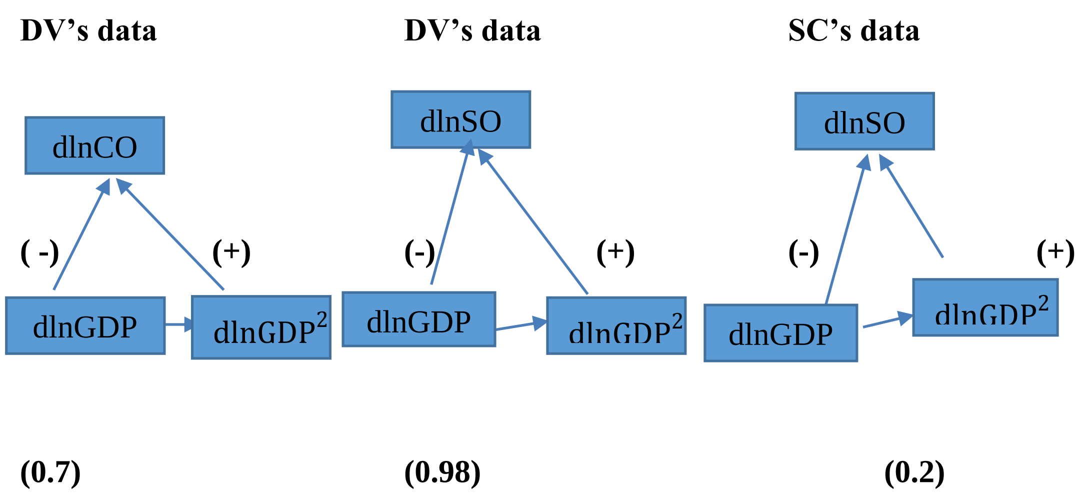


Notes: dlnSO2 = the first difference of the natural log of per capita sulfur dioxide emissions; dlnCO2 = the first difference of the natural log of per capita carbon dioxide emissions; dlnGDP = the first difference of the natural log of per capita GDP; dlnGDP^2 = the first difference of the square of natural log of per capita GDP.

Figure III.6. DAGs Generated Using the PC Algorithm (First Differenced Stationary Data)

suggests that higher levels of income push down carbon dioxide emissions and sulfur dioxide emissions. This relationship is also observed for the DV Sulfur and SC dataset at either a higher level of significance or lower prune value.

The DAGs for stationary data, using the PC algorithm, provide stronger evidence for an EKC relationship than the DAGs for non-stationary data, comparing figures III.5 and III.6. However, the levels of significance at which such a relationship is found varies for each dataset, especially when the LiNGAM algorithm is used. Previous knowledge cannot be used to place restrictions on the data within the LiNGAM setup.



Notes: dlnSO2 = the first difference of the natural log of per capita sulfur dioxide emissions; dlnCO2 = the first difference of the natural log of per capita carbon dioxide emissions; dlnGDP = the first difference of the natural log of per capita GDP; $dlnGDP^2$ = the first difference of the square of natural log of per capita GDP.

Figure III.7. DAGs Generated Using the LiNGAM Algorithm (First Differenced Stationary Data)

The result from the LiNGAM algorithm varies from the PC algorithm; the direction of causality between per capita GDP and per capita GDP^2 is clear. The LiNGAM algorithm exploits the non-Gaussian nature of the data to identify causal relationships (Moneta et al. 2013).

Granger causality

While, the DAG approach is rooted in contemporaneous values of variables, the Granger causality approach to causality is based on the influence of lagged variables. Two alternate methods for estimating Granger causality are employed. The first is Hurlin's (2004) approach, which has been employed frequently in recent literature.

The first step is the testing of the homogeneous non-causality hypothesis; the assumption under the null hypothesis is that there is no causal relationship between pollution emissions and GDP for all countries. The alternative hypothesis is that there is a causal relationship between pollution and emissions for at least one country in the sample. The values of the coefficients of the model are allowed to vary across the different panels. The statistic used to test for causality is an average of individual Wald statistics that are used to test for Granger causality for each country. The following model is fit to the data. The two variables considered, x and y (in this analysis, per capita emissions and pollution emissions), are assumed to be covariance stationary. For each country i=1………N, at time t=1,……,N, the following model is considered (Hurlin and Venet 2008):

(III.19) $$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)}\, y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)}\, x_{i,t-k} + \varepsilon_{i,t}.$$

The lag lengths are assumed to be identical across all cross-sectional units. The homogenous non-causality hypothesis is represented by the following equation, III.20:

(III.20) $$\mathrm{H}_0\!: \beta_\mathrm{i} = 0 \forall i = 1, \dots .N.$$

Under the alternative hypothesis, β_i is allowed to vary across groups; it is assumed that there is a causal relationship between panels of variables in the data. The test statistic, the Wald statistic, is an average of individual Wald statistics for each country. An individual Wald statistic is associated with a null hypothesis:

(III.21) $$\mathrm{H}_0\!: \beta_\mathrm{i} = 0.$$

Each of these statistics, under the null hypothesis of non-causality, converge to a chi-square distribution. Therefore, when N and T tend to infinity, this average Wald statistic follows the standard normal distribution (Hurlin and Venet 2008):

(III.22) $$\mathrm{Z}_{\mathrm{N,T}}^{\mathrm{Hnc}} = \sqrt{\frac{\mathrm{N}}{2\mathrm{K}}}\,(\mathrm{W}_{\mathrm{N,T}}^{\mathrm{Hnc}} - \mathrm{K}) \rightarrow \mathrm{N}(0{,}1).$$

If the time dimension, T, is fixed, the individual chi-square distributions need not converge to a universal chi-square statistic. Hurlin (2004) then proposes an approximate standardized statistic $\widetilde{Z}_{N,T}^{Hnc}$ (Hurlin and Venet 2008):

(III.23) $$\widetilde{\boldsymbol{Z}}_{\boldsymbol{N,T}}^{\boldsymbol{Hnc}} = \frac{\sqrt{N[W_{N,T}^{Hnc} - N^{-1}\sum_{i=1}^{N} E(W_{i,T})]}}{\sqrt{N^{-1}\sum_{i=1}^{N} Var(W_{i,T})}}.$$

The entire Granger causality test is carried out by using the program written by Dumitrescu and Hurlin (2012). The results of the Granger causality tests are presented below in Tables III.10, III.11 and III.12. The selection of the lag length is not clear;

therefore, following Dumitrescu and Hurlin's (2012) work, results are presented for the first three lags. The sizes of their dataset and the datasets considered in this study are similar.

Table III.10. DV Dataset Carbon Dioxide

	p[17]=1	**p=2**	**p=3**
H0: Carbon dioxide emissions does not Granger cause per capita GDP			
Wald	2.231	3.010	3.686
Z bar	4.173(0.000)[18]	4.844(0.000)	4.029(0.000)
Z tilda	3.588(0.000)	1.876(0.061)	0.822(0.411)
H0: GDP per capita does not Granger cause carbon dioxide emissions			
Wald	2.699	3.675	5.712
Z bar	5.761(0.000)	8.034(0.000)	15.926(0.000)
Z tilda	5.022(0.000)	3.286(0.001)	4.247(0.001)

[17] p here refers to the lag length; the choice of lag length is based on Hurlin and Venet (2008).
[18] The values in parentheses are the p values.

Table III.11. DV Dataset Sulfur Dioxide

	p=1	p=2	p=3
H0: Sulfur dioxide emissions do not Granger cause GDP per capita			
Wald Statistic	0.985	2.193	3.601
Z bar statistic	-0.0531(0.958)	0.946(0.344)	3.606(0.000)
Z tilda statistic	-0.336(0.736)	0.147(0.882)	0.693(0.489)
H0: GDP per capita does not Granger cause sulfur dioxide emissions			
Wald Statistic	3.049	4.054	5.491
Z bar statistic	7.10(0.000)	10.064(0.000)	14.947(0.000)
Z tilda statistic	6.225(0.000)	4..178(0.000)	4.957(0.000)

Table III.12. SC Sulfur Dataset

	p=1	p=2	p=3	p=4
H0: Sulfur dioxide emissions do not Granger cause GDP				
Wald	1.163	2.431	3.778	4.920
Z bar	0.992(0.321)	3.720(0.000)	8.201(0.000)	11.191(0.000)
Z tilda	0.4196(0.675)	0.900(0.369)	1.351(0.177)	1.110(0.261)
H0: GDP per capita does not Granger cause sulfur dioxide emissions				
Wald	1.140	2.881	4.509	5.941
Z bar	2.445(0.014)	7.575(0.000)	15.894(0.000)	23.613 (0.000)
Z tilda	1.681(0.093)	2.515(0.012)	3.413(0.001)	3.493(0.001)

The direction of causality based on the results in table III.10 for DV's dataset is ambiguous at the 5% level of significance and one lag specification; there is a bidirectional relationship between emissions and income (the hypothesis of non-causality is rejected in both directions). However, for two and three lags, the relationship is unidirectional; per capita GDP Granger causes emissions (the hypothesis can only be rejected in one direction). Tables III.11 and III.12, based on the z statistic, support a bidirectional causality relationship between emissions and per capita GDP for lags greater than two (the hypothesis of non-causality is rejected in both directions). The z tilda statistic supports a unidirectional causality relationship; income Granger causes emissions (the hypothesis of non-causality can only be rejected in one direction). An alternate estimation of the panel Granger causality test is presented appendix A.V... This test is based on the PVAR model estimated by equation III.18. The results from this model generally indicate that the direction of causation between variables is bidirectional.

Results

The DAG and the Granger causality approaches have been used to examine the direction of causality between variables. The data have been transformed by the Helmert procedure and taking first differences. These procedures control for fixed effects and make the data stationary, reducing the risk of spurious correlations.

The results of the DAG analysis, a part of the VARLiNGAM procedure, indicate that there is a clear unidirectional causal relationship from GDP to pollution emissions.

This result is true across all three datasets and the two pollutants sulfur dioxide and carbon dioxide. The DAGs were also generated with different lag lengths: the unidirectional relationship between income and emissions appears to be robust to different lag specifications. This result provides information about the possible SVAR model, allowing for possible policy recommendations in contemporary time. Carson (2010) states by using a reduced-form regression equation we cannot conclude that changing values of per capita GDP lead to changes in pollution emissions. However, the VARLiNGAM approach used here provides evidence that values of pollution emissions are changed by changing values of per capita GDP, in contemporary time.

Hurlin's (2004) approach to causality, like the DAG approach, finds a strong unidirectional causal relationship from GDP to sulfur dioxide emissions. However, the results for carbon dioxide emissions are more ambiguous, at one lag specification; at the 5 % percent level of significance there is a bidirectional causal relationship between emissions and income. At two and three lag specifications, the relationship is a unidirectional causal relationship from GDP to carbon dioxide emissions.

On the basis of these tests, it is difficult to decide if the relationship between pollution emissions and GDP per capita in DV's carbon dioxide dataset is unidirectional or bidirectional. The relationship between sulfur dioxide emissions and per capita GDP is unidirectional, and the direction of causation is from emissions to GDP. Most Granger causality studies within the EKC context focus on a single country; therefore, it might not be appropriate to compare the results of those studies with the results from this study. However, the study by Coondoo and Dinda (2002), which examines Granger causality results between emissions and GDP per capita across various groups of countries, finds that for the developed countries in USA and Europe), the causality relation is from emissions to income. The DV dataset, which is comprised of OECD countries, does not support this result. There does not appear to be a panel analysis of the causal relationships between sulfur dioxide emissions and per capita GDP.

Finally, the DAGs generated using the untransformed data reveal a positive causal relationship between GDP and emissions and a negative relationship between GDP squared and emissions; supporting the EKC hypothesis only at high levels of significance. The level of significance was taken to be 0.2 for DV's carbon dioxide data set. The significance level had to be increased to 0.4 to observe a relationship between GDP, GDP squared and sulfur dioxide emissions for Sulfur data sets's data. The results at these significance levels support a U-shaped relationship. The OLS regression is used to determine the sign of the relationship between the variables. These results are identical to the OLS results obtained by Stern (2010). The DAGs are also generated with stationary data. The LiNGAM algorithm was also used to generate the casual relationship. The alternate specifications also support a U-shaped relationship between emissions and income. However, the levels of significance at which this relationship is found to be significant for the LiNGAM procedure is low. The greater ability of the LiNGAM method to identify causal relationships between variables, when compared to the PC algorithm, is revealed in the comparison of figures III.6 and III.7.

Limitations

Among the limitations of this analysis, two are particularly worth highlighting. First, the Granger causality test is based on the assumption that the residuals are distributed normally; the test statistic might, therefore, not follow the Chi-Square distribution. The PC algorithm used to generate the graphs also assumes that the variables are distributed normally. However, the SK test rejects the assumption that the residuals are normally distributed.

Secondly, this study is based on previously used datasets; the DV and SC datasets do not consider any additional variables other than per capita emissions and GDP. Additional factors may well influence pollution; these factors are not controlled, since this study is based on previously used datasets. Harbaugh et al.'s (2002) dataset does contain information on additional variables; however, due to the unbalanced nature of the data, extensive analysis is not carried out on this data. However, the DAG approach assumes that all variables are included in the model (causal sufficiency).

Conclusion

The two approaches to causality explored in this chapter are based on different definitions. The Granger causality approach is based on the predictive definition of causality, whereas the DAG approach is based on the manipulative definition of causation. The Granger causality approach is an indicator of the ability of one variable to predict another. Whereas the DAG approach is rooted in contemporaneous time and is an indicator of whether changing contemporaneous values of one variable has an impact on the values of the other variable.

The main contribution of this essay is the application of the VARLiNGAM approach to causality analysis within the EKC. By using DAGs, we can convert the VARs into SVARs by using directed acyclical graphs. Therefore, utilizing the DAG approach, policy recommendations can be made based on the results. In this context, there is evidence to suggest that current values of pollution emissions are changed by changing current values of GDP per capita.

Moreover, using the results from the VARLiNGAM procedure, the DAG using the PC algorithm can also be used to test causal relationships associated with the EKC hypothesis. The causal relationship between pollution emissions and GDP is positive, whereas the relationship between GDP squared and income is negative. This supports a U- shaped relationship between pollution emissions and income. The LiNGAM model also supports these results. This study also highlights the greater ability of the LiNGAM process to identify causal relationships when compared to the PC algorithm.

More generally, DAGs provide a useful tool to test and represent causal relationships between environmental and economic indices, thereby providing a tool to empirically test theoretical frameworks within environmental economics.

Granger causality, on the other hand, as mentioned earlier, is based on the ability of the past values of one variable to predict another variable; therefore, the fact that there is a certain amount of correlation between the variables, could also lead to the conclusion that one variable Granger causes the other. Such analysis gives us insights into why certain bidirectional causal relationships between income and pollution emissions could not be rejected in the case of carbon dioxide. One of the contributions of this essay is to use Hurlin's (2004) approach to test for panel Granger causality.

Both the Granger causality approach and the DAG approach incorporate Hume's definition of causality. Therefore, both methods need to be used to understand the causal relationships between variables. The DAG approach can be used to provide evidence of an EKC relationship.

CHAPTER IV

EXAMINING THE ROLES OF THE SOCIAL FORESTRY PROGRAM AND THE JOINT FOREST MANAGEMENT PROGRAM IN THE INDIAN FOREST TRANSITION

Over the past twenty years, the forest area in India has stabilized. Many countries have experienced the phenomenon of traversing from net deforestation to net afforestation, leading to the formulation of the Forest Transition (FT) theory. Specifically, the FT theory predicts various changes in forest cover over time: (1) initially high forest cover and low deforestation, (2) accelerating and high deforestation, (3) slow-down of deforestation and forest cover stabilization, and (4) a period of reforestation (Angelsen 2007).

According to Mather (2007), India has experienced the first two stages of the FT and is said to be in the third or the fourth stage of the FT theory. The majority of forest area in India is under state control; private participation in forest management has generally been discouraged. Moreover, the focus of forest management was initially on producing commercial timber rather than producing fuelwood, fodder and small timber for the local population. The Joint Forest Management (JFM) and the Social Forestry Programs have been initiated to focus on these needs.

The aim of this analysis is to provide possible explanations for Indian FT and to examine the roles of these programs in the Indian FT. These two programs signaled a change in property rights of forest resources; the policies on which the programs are based focus on needs of the local population and the decentralization of forest resources. These policy measures, which signaled the move towards decentralization and greater community rights, coincided with the FT.

This analysis is divided into the following sections. The first section is a description of recent forestry trends in countries that have experienced an FT in Asia, and provides the motivation for the proposed analysis. The second section focuses on FT theory. The third section is an overview of the forest policy in India, and how it has changed over time; focusing particularly on the Social Forestry Program and the JFM Program. The fifth section is an exploration of the role of these programs in the FT of India. The sixth section is the conclusion.

Recent Trends in Forestry

India experienced deforestation beginning in the 1800's. However, the forest area has stabilized in the recent past. The forest transition experience in both China and Vietnam has been more pronounced than the Indian forest transition; table IV.1. describes the long-term trends in forestry in these three countries.

Table IV.1. Long-Term Trends in Forest Cover (Millions of Hectares)

China		India		Vietnam	
Year	Forest Cover	Year	Forest Cover	Year	Forest Cover
		1880	102.7	1880	25.0
		1920	94.8	1920	20.7
1949	102.3	1950	82.5	1950	18.9
1977–81	95.6	1970	74.3	1970	16.4
1989–93	108.6	1980	64.6	1980	14.8

Source: (Mather 2007) Table 2 pg. 493 adapted from (India,Vietnam-Flint and Richards 1994) and (China-Fang et al. 2001). Recent Asian forest transitions in relation to forest-transition theory published in the *International Forestry Review* 9:491-502, reproduced with permission from Commonwealth Forestry Association.

While the sources and definitions of forest have changed over time, it is apparent that all these countries have experienced deforestation. However, beginning in the 1990's the forest area in all three countries has increased. Figure IV.1 shows the increase in forest area in India over the past twenty years. There is some controversy on whether this change is a result of increasing natural growth forest or whether it is due to the increase in plantation forest. Puyravaud et al. (2010) found empirical evidence that suggests that although total forest area based on forest cover might be increasing, the area of natural forests is actually decreasing; most of the increase in forest area is due to the growth of tree plantations.

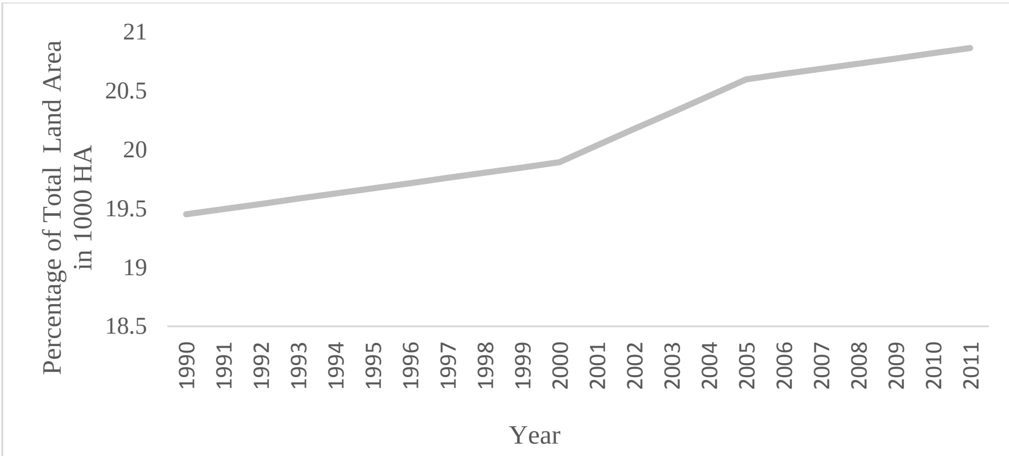


Figure IV.1. Percentage of Total Forest Area in 1000 HA[19]
Source: FAOSTAT 2014a

There has been an increase in demand for forestry products with an increase in population. Table IV.2. below represents the trends in forestry products[20]. The forest products are chosen based on products considered in Guha (1983). The demand for forest products such as pulpwood and fuelwood has increased over time. The products considered are fuelwood (charcoal and non-charcoal), paper and paper board, wood pulp, round wood and industrial round wood. These figures are five-year averages. Table IV.2. below reveals that there has been an increase in the production across all forest products. There is a particularly sharp increase in the production of wood pulp and paper and paperboard which uses wood pulp for its manufacture.

[19] FAOSTAT 2014a Accessed data in January 2014. Website last accessed on 23rd May 2014. (http://faostat.fao.org/site/377/default.aspx#ancor).
[20] FAOSTAT 2014a Accessed data in February 2014, Website last accessed website on 23rd May 2014 (http://faostat.fao.org/site/626/default.aspx).

Table IV.2. Forest Products

	Wood Fuel (C)	Wood Fuel (NC)	Wood Fuel	Industrial Round Wood	Round Wood	Paper and Paper Board	Wood Pulp
		100,000's m3				1000's tonnes	
1961–1965	48.580	1566.822	1615.402	75.262	1690.664	541.020	30.600
1966–1970	54.034	1742.727	1796.761	116.278	1913.039	751.860	78.000
1971–1975	60.970	1966.437	2027.407	147.684	2175.091	861.800	266.620
1976–1980	66.939	2158.961	2225.900	183.168	2409.068	985.600	451.080
1981–1985	73.911	2383.803	2457.714	221.598	2679.312	1430.200	682.000
1986–1990	80.836	2607.163	2687.999	242.186	2930.185	1977.800	946.400
1991–1995	85.934	2771.602	2857.536	246.906	3104.442	2680.000	1104.200
1996–2000	83.420	2690.380	2773.800	190.742	2964.542	3381.205	1437.000
2001–2005	89.586	2889.349	2978.935	205.908	3184.843	4419.001	1855.080
2006–2010	92.559	2985.250	3077.809	231.922	3309.731	8188.144	2307.600

Source: FAOSTAT 2014b

The Forest Transition

Mather and Needle (1998) formulate the FT model by documenting forestry trends across various countries in the world. This documentation of forestry rates provides evidence for the FT model. Mather (2007) discusses the forestry experience in Asia focusing on China, Vietnam and India; all three countries have experienced a forest transition. According to his paper, the FT in India occurred in the 1990s. He considers a number of possible explanations for the forest transition and concludes that radical policy measures are the possible explanation for FT in Asia. In the paragraphs that follow, we summarize the various theories that been proposed to explain the FT process.

The Environmental Kuznets Curve (EKC) hypothesis

The EKC hypothesis predicts a U-shaped relationship between income and environmental harm. Applied to deforestation this could mean that as income increases, deforestation first increases and then decreases. Mather et al. (1999) observe that while there is longitudinal evidence for an EKC for deforestation, the U-shaped curve seems to be linked to time rather than income. It is difficult to build a causal story between income and deforestation.

Cropper and Griffiths (1994) provide a theoretical explanation for the EKC relationship in forestry. First, rising income leads to an increase in demand for logging and fuelwood. However, with continued increases in income there is a decline in demand for fuelwood and agriculture, resulting in the downward sloping relationship at higher income levels. At the micro–scale, Panayotou and Sungsuwan (1989) find evidence that suggests that increases in income lead to a decrease in demand for fuelwood. In the case of India, due to rapid increases in population, the overall demand for fuelwood has increased.

There have been many investigations interested in examining empirical evidence for such an EKC relationship in the forest sector. Conclusions from empirical investigations into this area vary: Bhattarai and Hammig (2001, 2004) and Cropper and

Griffiths (1994) find evidence for an EKC in deforestation, while Koop and Tole (1999) found no evidence for this kind of relationship (Mather 2007).

These empirical EKC studies also estimate the turning point in the Environmental Kuznets Curve (EKC). Within the Asian context, Bhattarai and Hammig (2001) state that the FT has taken place in countries where the GDP per capita exceeds US $7750 (1985 data). However, as Mather (2007) points out, there are countries in Asia where the FT has occurred in the $2000–$4000 range. India's per capita GDP measured in current dollars is still lower than US $7750. Moreover, other countries in Asia, for example, Malaysia and the Philippines, are economically more prosperous than India but have yet to experience an FT (Mather 2007).

Borlaug hypothesis

Another explanation offered to explain the FT phenomenon is known as the Borlaug hypothesis. It has been argued by Norman Borlaug and others that the intensification of agriculture leads to greater land being available for alternate uses, one of them being forestry (World Resources Institute 1986; Rudel and Horowitz 1993; Southgate 1998; Rudel 2001). In an attempt to capture this effect, a cereal index or a time trend is included in empirical studies that examine the factors that influence deforestation. The results from these studies are inconclusive (Culas 2007). Theory also suggests that the impact of technological change on the extent of agricultural land depends on the type of technical change (Angelsen 2001). Foster and Rosenzweig (2003), in their study of a forest growth, using a cross-section of 235 villages across

India, do not find empirical evidence to support the Borlaug hypothesis. Specifically, they find no empirical evidence to suggest that increases in agricultural productivity due to the Green Revolution led to less cultivated acreage or more forest growth (Foster and Rosenzweig 2003).

However, Mather (2007) found that the agricultural area in India had stabilized, and the increases in rice and wheat yields were higher for the FT countries than for the non-FT countries; however, this effect was confined to rice and wheat yields. FAO data indicate that the price of rice, wheat and sorghum in India decreased during the 1990's.

The ecosystem service hypothesis

The basis for the "Ecosystem Service Hypothesis" is degradation of forest area. Forest land degrades to an extent where the local population can no longer depend on it to provide certain commodities and services. This leads to the abandonment of forest area and the regeneration of the forest area (Satake and Rudel 2007). Mather (2007) observes that the Asian forest transition occurred in countries at rates at relatively high percentages of forest cover when compared to the FT experience in the European and North American countries.

The forest scarcity hypothesis

A fourth theoretical explanation has its foundations in a microeconomic model and is known as the "Forest Scarcity Hypothesis'' (Hyde 1980). This hypothesis has been recast by Rudel (1998) and Rudel et al. (2005). It states that as forest cover declines, forest products become scarcer and the prices of these products increase. This provides incentives for people to afforest and protect existing forests. According to Satake and Rudel (2007), evidence supporting this hypothesis has been found in West Africa (Fairhead and Leach 1995), Philippines (Walters 1997) and India (Rush 1991).

Foster and Rosenzweig's (2003) analysis also finds evidence for the forest scarcity hypothesis in India. They find that growing income and population lead to an increase in the aggregate demand for forest products. This demand, in the absence of imports, must be met by locally grown wood products; this, therefore, leads to an increase in forest area.

An extension of Foster and Rosenzweig (2003) and an estimation of the impact of community forestry on the demand for fuelwood are provided by Bandyopadhyay and Shayamsunder (2004). In their analysis, they try to determine the factors that influence participation in community forestry and the impact of such participation on fuelwood consumption. They find that there is a positive correlation between fuelwood consumption and household participation in community forestry. They find that household participation is strongly correlated with scarcity. Factors that influence village participation in community forestry are proximity to forests, leadership and fuelwood dependence.

Finally, some authors have looked at changes in relative prices to explain the FT. Barbier et al. (2010), based on the work of Alexander Mather, offer an approach to develop a more comprehensive theory of forest transition. According to them, factors that affect the transition of a country, such as relative land values, cannot be ignored.

Similarly, Foster and Rosenzswieg (2003) consider the average price of land in their analysis of land use. After including other factor prices such as the average price of labor, they find that increases in factor costs (which are rising since the 1960’s) could not be the cause of increases in forest area.

The two radical policy programs suggested by Mather (2007), the Joint Forestry Program and the Social Forestry Program, explored in greater detail in the next section, are institutional responses to scarcity in forest products in India. These two forest policies focused on the needs of the local population and decentralization of forest resources.

Mather (2007) observes that the time period for Foster and Rosenzweig’s (2003) study, 1970–2000, is also the time period in which both the Social Forestry and JFM Programs were initiated. To understand the policy context to these programs, a brief historical background on Indian forest policy is provided. Figure IV.2 is a map of India with the different states and forest areas.

History of Forestry Policy in India

Colonial forest policy (1800–1947)

State control of Indian forests in the pre-colonial period was restricted to certain products and specific instances (Bhat et al. 2001). Not much value was placed on this resource until well into the 19th century. With the depletion of oak forests in England and Ireland, teak grown in the Western Ghats (green areas in Kerala, Karnataka, Goa and Maharashtra) region served as a durable substitute for shipbuilding timber (Guha 1983). However, the movement towards a general policy of state control of forests gained momentum only in the last decades of the nineteenth century. Rapid expansion of the Indian railways led to an increase in the demand for railway sleepers and the realization that the forest resource is finite and, therefore, is to be administered. This, in turn, led to the establishment of The Forest Department (Guha and Gadgil 1989).

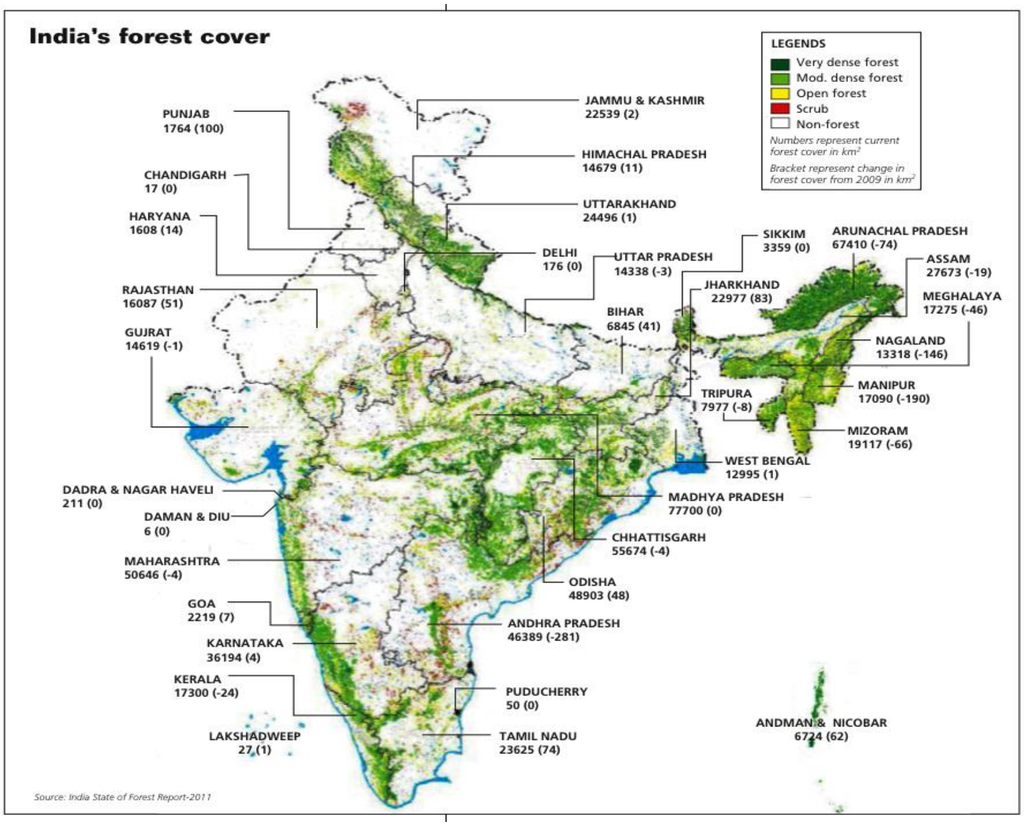


Figure IV.2. Forest Areas in India

Source: India State of the Forest Report 2011(Figure 2.6.1 Forest Cover Map of India, pg 17). Image reproduced from K.S. Srivastava (2012) “India’s Forest Cover Declines” Feb 8th 2012 Science and Environment Online Down to Earth, Reproduced with the permission of Science and Environment Online Down to Earth retrieved from http://www.downtoearth.org.in/content/india-s-forest-cover-declines?quicktabs_1=0

This began the large-scale state monopoly of forests, which gained legal credibility under the stringent provisions of the Indian Forest Act of 1878. The local populations, who depended on forests for a number of needs, were allotted a specific quota of timber and fuel. This quota led to the exclusion of the local agrarian population from the use of the forests. The forest dwellers' access to the forest resource was looked upon as a privilege rather than a right (Guha 1983).

Socially, the property rights of the forest dwellers diminished to a marginal and inflexible claim: physical access to forests and pasture was denied (Guha and Gadgil 1989). This shift in management had ecological implications as well: species composition changed from mixed species into a single-species forest. These single-species forests could no longer meet fuel, fodder and small timber needs of the local populations (Guha and Gadgil 1989). By 1947, according to Lal (1989), the percentage of area under reserved forests was 96.79% (Bhat et al. 2001). The forest dwellers' right to forest products diminished due to colonial policies.

Post-Colonial forest policy

Independence initially did not lead to an increase in the property rights of the local population. The 1952 Forest Policy was very similar in spirit to The Forest Act of 1878. It stated that village communities in no event should be permitted to use the forest at the expense of national interest. Emphasis was also placed on the conversion of "low"-value mixed forests into "high"-value mixed plantations. Scientific forestry was associated with rising industrial plantations (Saxena 1997).

Firewood and fuelwood, classified as minor forest products, were mainly ignored for a number of years. However, there was increasing demand for these products from individuals who had a stake in the forests. The National Agricultural Policy of 1976 directly addresses these needs. The aim of this policy was to provide for the fuelwood and fodder needs of the local dwellers (Saxena 1992a). Empirical evidence that the Social Forestry Program, an outcome of this policy, might be successful is provided by Foster and Rosenzweig (2003); empirical evidence from this study suggests that one pathway for FT may have been the raising of plantations for fuelwood. The Social Forestry Program and its possible impact on forest area are discussed in the following section.

Though there were certain specific instances where community forestry were promoted, state control of national forests continued until the 1980's. The major change in Indian forestry policy occurred in the 1980's with the National Forest Policy when community requirements of fuelwood, fodder, minor forest produce and construction timber were given importance. This led to the creation of new institutions, a new form of governance which was supposed to lead to the creation of community property rights to forest produce (generally outside forests) under the Social Forestry Program and forest area under the JFM program.

The Social Forestry Program

The goal of the Social Forestry Program is to the meet the timber, fuelwood and fodder needs of the local population and, in the process, also regenerate and improve tree cover on degraded and common lands (Puttaswamiah 2009). The concept of social forestry was proposed as early as 1897. However, real progress began to be made only in the 1980’s (Sharma 1993). The National Commission on Agriculture (NCA) in 1976 provided the framework for the creation of the Social Forestry Program; the formal origins of the Social Forestry Program can be traced to this policy (Arnold 1991). The program further gained momentum with the setting up of the National Wasteland Development Board in 1985 (Sharma 1993). The Social Forestry Program is made up of the following components:

- Farm Forestry: This program encourages farmers to grow trees on the peripheries of their fields (Puttaswamiah 2009). The Farm Forestry program was also encouraged by the National Forest Policy of 1988. This policy advocates that, as far as possible, forest-based industries should obtain their raw materials by establishing direct links with farmers (Sharma and Kohli 2013).
- Extension Forestry: the goal of this program is the reforestation of common lands. It promotes mixed forestry on common lands, the raising of shelter belts and planting trees along roads, railway lines and riverbanks (Puttaswamiah 2009).
- Reforestation of degraded forests: This component of the program encourages the growth of trees in degraded areas to meet the fuelwood needs and small timber needs of the local population (Puttaswamiah 2009).
- Urban forestry or recreational forestry: Planting of trees in urban areas to meet the recreational needs of urban dwellers (Puttaswamiah 2009).

The Farm Forestry component of the Social Forestry Program is confined to activities undertaken by farmers, mainly on their own private lands (Saxena 1997). Whereas the remaining components of the program are on public lands, these components of the Social Forestry Program remained largely unsuccessful because they depended on voluntary contributions of labor and capital from local communities (Saxena and Ballabh 1995 in Rangan and Lane 2001). The property rights to the forest products for the poor among these local communities were not certain. The Forest Department continued to be extremely powerful.

The Social Forestry Program was generally confined to village and private lands. The Social Forestry Program was not implemented on forest lands, except on a small scale in SIDA projects in Bihar and Orissa, as such lands were in the past used for producing timber (Saxena 1997).

The Social Forestry Program basically tried to curb deforestation by providing incentives for growing forest products on non-forested lands. Afforested forest produce on these lands acted as a substitute to the products consumed in local areas. The goal of this program was to provide local populations with property rights to forest produce generally grown outside designated forest areas.

The principal incentive provided by the state forest departments under the farm forestry program is subsidized by free seedlings. In certain instances, as in the case of West Bengal, degraded land was allotted to the poor for the growth of plantations.

Market forces provided incentives for the growth of Farm Forestry. The scarcity of raw materials experienced by forest-based industries created a demand for forest products (Foster and Rosenzweig 2003). The price of these products increased, providing an incentive for the growth of plantations.

Evolution and patterns in the Social Forestry Program

According to Tiwary (1998), the Social Forestry Program received external funding from a number of sources including The World Bank, Danish International Development Assistance (DIDA), Swedish International Development Cooperation Agency (SIDA), Official Development Assistance (ODA) and the European Economic Community (EEC). Further, according to Saxena and Ballabh (1995), there was an overall increase in area under tree crops (Rangan and Lane 2001).

Initial publications of the State of Forest reports (published by the Forest Survey of India [FSI]) provide some information on the growth of plantations and afforestation. However, ever since the publication of the 2001 State of Forest Report, information on tree cover is provided instead. Tree cover is defined as an area of trees which are less than one hectare. If this area were more than one hectare, it would be considered as forest cover. Therefore, in this analysis the relationship between percentage changes in forest cover and tree cover will be examined.

Both figures IV.3 and IV.4 present the increase in plantations since the first planning period; figure IV.3 presents the cumulative increase in plantation area in 1000's of hectares. Moreover, figure IV.4 represents the annual average area of plantations raised in the different planning periods. It is clear that area under plantations increased rapidly since the 1980's. This increase in plantation area is an increase in plantations due to The Social Forestry Program.

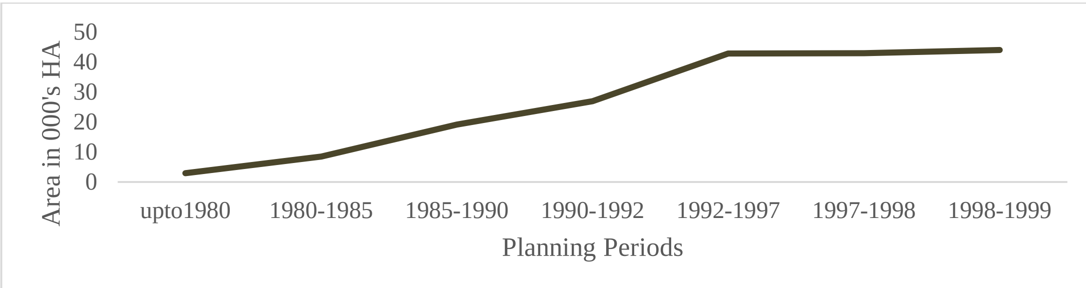


Figure IV.3. Cumulative Increase in Plantation Area Raised by the Forest Department
Source: State of Forest Report 1999

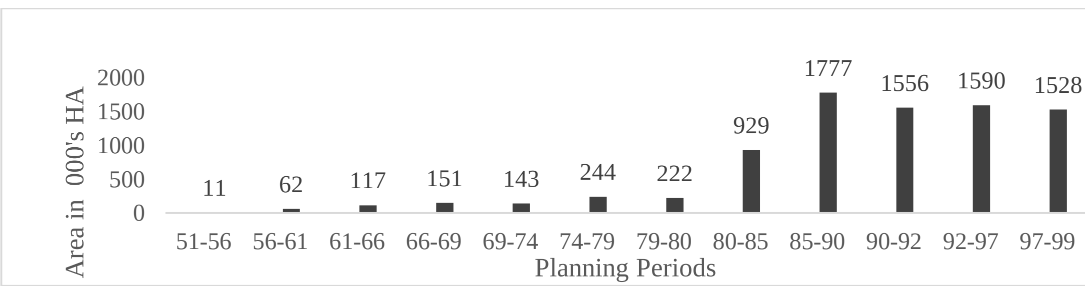


Figure IV.4. Annual Average Increase in Plantation Area in Different Planning Periods
Source: State of the Forest Report 1999

The percentage of total geographical area under plantation cover (table IV.3) due to afforestation activities by the state forest departments is used as a measure of the success of the Social Forestry Program. Among the larger states, based on percentages under the different components in table IV.4, the success of the Social Forestry Program in Haryana, Punjab, Gujarat, Karnataka and West Bengal might be due to the success of the farm forestry project in these regions (the states with the largest planted areas). These states are generally characterized by commercial and monetized agriculture (Saxena 1992a).

Table IV.3. Percentage of Total Geographical Area under Plantation Area Across States (1999)

States and Union Territories	Total Area (Million Hectares)	Area under Plantation (Million Hectares)	Percentage of Area under Plantation
Gujarat	19.600	2.980	15.204
Haryana	4.420	0.743	16.804
Himachal Pradesh	5.570	0.719	12.916
Karnataka	19.180	2.160	11.262
Kerala	3.890	0.688	17.686
Orissa	15.570	1.827	11.734
Punjab	5.040	0.512	10.166
Tamil Nadu	13.000	2.200	16.923
Uttar Pradesh	29.440	4.150	14.096
West Bengal	8.870	1.150	12.965

Source: Adapted from information in the State of the Forest Report 1999

According to Saxena (1992a), the supply of Eucalyptus, and hence a large percentage of the area under forest plantation, is dependent on market incentives. Supply from farmers in Haryana, Punjab and Gujarat was more price elastic than the supply from farmers in Karnataka and West Bengal (Puttaswamiah 2009). Eucalyptus

Table IV.4. Percentages by Different Components of Social Forestry (Externally Aided)

	Village Woodlots	Strips Plantations	Reforestation of Degraded Forests	Farm Forestry
Gujarat	11.182	5.751	9.585	73.482
Bihar	18.343	0.592	38.462	42.604
Uttar Pradesh	8.075	0.621	0.000	91.304
Andhra Pradesh	16.556	2.649	9.272	71.523
Karnataka	16.779	2.685	0.000	80.537
Rajasthan	3.361	3.361	16.807	76.471
Himachal Pradesh	36.283	0.000	4.425	59.292
Tamil Nadu	37.554	4.348	2.174	55.978
West Bengal	6.452	21.505	16.129	55.914
Kerala	16.471	2.353	0.000	81.176
Orissa	34.247	0.457	24.658	40.639
Maharashtra	41.975	3.704	0.000	54.321
Haryana	17.647	14.706	23.529	44.118
Jammu and Kashmir	11.364	6.818	38.636	43.182
All India	19.964	4.053	12.314	63.674

Source: converted into percentages table 1.2 :Area Brought under the Externally Aided Social Forestry Projects in India Statewise (Area in Thousand Hectares page 10, Puttaswamiah (2009), original source Forestry Statistics India (1995), (adopted from Compendium of Environmental Statistics (1997)).

plantations, in these three states, were grown in regions where land productivity is high. These plantations were not served by a paper mill, or there were far too few paper mills in the area. In Karnataka, the land productivity on which the plantations were grown was not high. There were many paper mills to buy paper. In West Bengal, the Eucalyptus plantations were grown on degraded forests. In Haryana, Punjab, Gujarat and Karnataka, the Eucalyptus plantations were remote from forest areas (Saxena 1992a) in Puttaswamiah (2009). The main incentive for growing Eucalyptus was market demand from forest-based industries.

The tree species of choice in the farm forestry program was Eucalyptus (State of Forest Report 1999). The choice of this species indicates the conflict between the proposed goals of the program and the market incentives that motivated the local community. The main motivation for growing Eucalyptus was cash; it was not for meeting the fuel and fodder needs of the household. The reasons given for the growth of Eucalyptus include shortage of labor, falling returns to crops in Haryana and Punjab, uncertain production of groundnut in Gujarat, low productivity of Sorghum and food grain crops in Karnataka and, finally in Bengal, the lands were unsuitable for crops and the labor was required for wage work (Saxena 1992a).

The community forest components of the Social Forestry program had limited success in certain states. According to Saxena and Ballabh (1995), the community forest components depended on voluntary contributions of labor and capital from local communities (Rangan and Lane 2001). The planting of a single tree species also reduced the variety of non-timber forest products (NTFP). The poor had little incentive to take part in these projects (Rangan and Lane 2001). The rights to the forest produce were not clearly defined (Saxena 1997).

Monetized agriculture was a necessary incentive for farm forestry. Village woodlots under the Extension Forestry component were developed in Orissa and Himachal Pradesh. Subsistence farmers, in states such as Orissa, Bihar and Madhya Pradesh, were mainly indifferent to the Farm Forestry Component (Saxena 1992a).

Another indicator of the success of the Social Forestry Program is the percentage increase in plantation cover since the 1980's. Table IV.5 is a list of states with the largest percentage increase in plantation cover since the 1980's

Table IV.5. States with the Largest Percentage Increase in Forest Area Since the 1980's

	Percentage increase since 1980
Andhra Pradesh	1583.339
Gujarat	1421.114
Jammu and Kashmir	1545.568
Maharashtra	1481.792

Source: Adapted from the State of Forest Report 1999

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Once again, the smaller states and union territories often have a percentage increase of more than 1000 percent. States and union territories with increases in forest area greater than 1000 percent are included. Andhra Pradesh, Gujarat, Maharashtra and Jammu and Kashmir are the relatively larger states that experienced the largest increases in plantation area. Based on table IV.5, the Farm Forestry component in Andhra Pradesh, Gujarat, Maharashtra and Jammu and Kashmir was large. In Jammu and Kashmir, the increase in plantation cover was due to the reforestation of degraded forests (Puttaswamiah 2009).

Comparison between forest area and indicators of growth of the Social Forestry Program

Table IV.6 examines the relationship between the percentage decadal rate of change in forest and plantation cover (1990–2000) due to afforestation schemes undertaken by the government across the different states and union territories. The correlation coefficients are positive and similar across both indicators of growth in Social Forestry.

Table IV.6. Percentage Increase in Plantation Area and Percentage Increase in Forest Area (1990–1999)

	Percentage change in Plantation area	Percentage change in Forest area
Andhra Pradesh	53.238	-8.325
Arunachal Pradesh	38.608	0.478
Assam	33.020	-9.663
Bihar	22.089	-1.738
Goa	34.649	-4.077
Gujarat	50.674	10.096
Haryana	62.978	41.598
Himachal Pradesh	42.205	-2.255
Jammu and Kashmir	52.190	0.083
Karnataka	30.942	0.838
Kerala	21.176	1.686
Madhya Pradesh	40.852	-1.032
Maharashtra	80.739	5.601
Meghalaya	50.711	-1.836
Mizoram	39.209	-2.852
Nagaland	30.412	-0.805
Orissa	47.889	-0.174
Punjab	29.295	17.422
Rajasthan	59.316	6.488
Sikkim	59.406	-0.192
Tamil Nadu	52.837	-3.730
Tripura	45.532	7.311
Uttar Pradesh	46.636	0.559
West Bengal	54.166	-0.383
Andaman &Nicobar	37.077	-0.237
Dader and Nager Haveli	48.148	-1.485

Source: State of the Forest Report 1999

Table IV.7. Relationship between Percentage Increase in Plantation Area and Forest Area (2000–2007)

	Percentage change in Tree Cover	Percentage change in Forest Area
Andhra Pradesh	-0.177	0.044
Arunachal Pradesh	0.086	-0.035
Assam	-0.209	0.095
Bihar	-0.321	0.266
Chhattisgarh	0.205	-0.032
Delhi	1.875	0.416
Goa	3.468	0.374
Gujarat	0.984	0.132
Haryana	-0.026	0.404
Himachal Pradesh	0.696	0.136
Jammu & Kashmir	1.796	0.141
Jharkhand	0.134	0.016
Karnataka	-0.251	0.087
Kerala	1.392	0.291
Madhya Pradesh	0.142	0.032
Maharashtra	0.115	0.125
Manipur	0.784	-0.034
Meghalaya	2.382	0.048
Mizoram	0.547	0.173
Nagaland	2.843	-0.037
Orissa	0.034	-0.004
Punjab	0.078	0.022
Rajasthan	0.575	0.103
Sikkim	0.679	0.061
Tamil Nadu	-0.125	0.112
Tripura	1.243	-0.090
Uttar Pradesh	0.033	0.331
Uttarakhand	0.477	0.049
West Bengal	-0.276	0.250
A. & N. Islands	-0.416	0.006
Chandigarh	4.000	0.308
Dadra & Nagar Haveli	0.019	-0.028

Source: Compendium of Environmental Statistics 2009 and State of Forest Reports 2001 and 2007

Table IV.7 examines the relationship between percentage rate of change in forest and tree cover (2000–2007) across the different states. While the increase in tree cover not only is due to the success of the Social Forestry scheme, this is the only easily accessible plausible measure. The correlations between both indicators of progress of the Social Forestry Program (plantation cover by the Forest Department and tree cover) and percentage change in forest cover are very similar and positive. The correlation coefficients between changes in tree cover and forest cover and change in plantation area and tree cover are 0.280 and 0.276, respectively, although these correlation coefficients are only significantly different from zero at a 20% level. Correlation is only a measure of association. It is not a measure of causation between the variables. A far more rigorous measure would be necessary to establish causation.

It is clear that, since the initiation of the Social Forestry Program, there has been an increase in plantation area. Further, growth in plantation cover might have a positive relationship with an increase in forest area. This could be due to two reasons, firstly, forest plantations acted as a substitute of raw materials for forest-based industries. And secondly, trees outside forests and plantations addressed the needs of the local population.

A number of criticisms have been leveled against the farm forestry program. One of drawbacks of the social forestry scheme is that the Farm Forestry component of the program attracts more commercial forestry rather than the growing of trees for fodder and fuelwood (Puttaswamiah 2009). Therefore, one of the primary causes of deforestation was not addressed by the program. The National Commission on

Agriculture hoped that farmers would grow trees for meeting fuel and fodder needs. However, trees were planted more for sale as poles and pulpwood rather than for meeting subsistence needs of the village population. Hence, the Social Forestry Program did not address the fodder and fuel needs of the local population. It promoted monoculture; trees were grown for their commercial rather than their ecological value. Eucalyptus, a non-native species, was generally found to be the most popular species. The Social Forestry Program seems to have addressed the needs of forest-based industries rather than the fuelwood, fodder and small timber needs of the local population.

There is also an opposing view that suggests that too much emphasis was placed on fuelwood and not enough emphasis on the fodder needs. The extraction of fuelwood might not be the primary cause of deforestation. According to Saxena (1997), forest dwellers often look for alternate sources for fuel. The impact of the Social Forestry scheme on the supply of fuelwood is not clear. A study in 2001 on the fuelwood demand and supply in India found that 72% percentage of the rural Indian population still depended on noncommercial energy (fuelwood, dung cake and crop residue) as their primary source of energy. However, the sources for the supply of this fuelwood have changed (Pandey 2002). The primary source is trees outside forest. The National Council of Applied Economic Research (NCAER) survey is a national survey; however, a study by Jaiswal and Bhattacharya (2013) analyzing the fuelwood dependence among villagers near Suhelwa Wildlife sanctuary found that nearly 87% of the households depended on the forest as their primary source of fuel.

Market incentives, combined with subsidized seedlings provided by the Social Forestry Program, led to large areas being afforested under the farm forestry program, mainly on private lands. There was a large demand for forest-based raw materials. This demand could not be met by forest lands; companies were not allowed to raise plantations and therefore had to rely on farmers to supply these products. Certainty in demand for forest produce and property rights to land areas seem to be the largest motives for the popularity of the farm forestry component of the Social Forestry Program.

Further, there is no evidence to suggest that increases in forested areas under the Social Forestry Program were due to community participation. Community woodlots planting was undertaken by the state forest departments; in the process, village lands were transferred to the forest departments. The limited success of the community woodlots in certain regions might be due to the transfer of village lands to the forest departments (Saxena 1997).

The Social Forestry Program led to large increases in planted area. Figure IV.2 suggests that areas afforested by the Forest Department increased rapidly after the 1980's. However, deforestation continued to take place. The Social Forestry Program did not fully address the NTFP needs of the local population, and this could have been a continued source of deforestation. The program failed to involve local communities in conservation (the non-farm forestry components of the Social Forestry Program). There was also lack of clarity on who owned the lands. The rules for distribution of the forest produce were not well defined. This further deterred any community involvement in the Social Forestry Program (Saxena 1997).

The JFM Program

The Joint Forest Management (JFM) Program was initiated as a community conservation policy. The need for community participation was recognized by the National Forest Policy of 1988. This policy facilitated people's participation in forestry. Under this program, local communities are encouraged to actively engage in the development and participation of the forest lands. In 1990, a circular was sent out to the state forest department, outlining the framework for the implementation of the JFM program. Bhat et al. (2001), Kumar (2002) and Mather (2007) suggest that the JFM could have halted the process of deforestation.

The Government of India defines JFM as a forest management strategy under which the government (represented by the Forest Department) and the village community enter into an agreement to jointly protect and manage forest lands adjoining villages and to share responsibilities and benefits (Damodaran and Engel 2003).

The framework for the JFM program is based on a pilot project carried out in Arbari in Midanpore in West Bengal in the 1970's. The local communities in these regions were involved in the protection of degraded forest lands dominated by Sal trees; in return for their services, they were promised twenty-five percent of the timber revenue from the final harvest (De 2003).

In the JFM program, local communities (generally known as village committees) form a partnership with the government to manage the resource and share the cost. The government is still considered as the owner of the resource, whereas village committees are considered to be the users. Local NGOs play the role of intermediaries between the government and village committees. The role of the village committees is to safeguard the forest resource from illegal exploitation and degradation by protecting the forest from fire, grazing and illegal harvesting. For these services, the village committees receive non-timber forest products and a part of the revenue from the sale of timber products. The JFM program differs from the Social Forestry Program; it allows local populations access to forest products grown within the designated forest areas. The local population is now granted user rights to forest products grown within designated forest areas.

At the time of the initiation of the Social Forestry Program, administrators were heavily influenced by Hardin's Tragedy of the commons. Nationalization or privatization were considered to be the only regime that led to efficient outcomes. Common Property regimes were not considered to be efficient (Saxena 1997).

The JFM program provides three types of products to village committees. The types of forest produce include immediate products like NTFP, grass, fuelwood, intermediate products from thinning and cultural operations and final products such as timber. The national JFM guidelines were issued in 1990; 22 states are implementing the program (Ministry for Environment and Forests). According to the Study on Joint Forest Management conducted by the Tata Energy Research Institute (TERI) for

Ministry of Environment and Forests (p. 14) in 2000, it was found that the overarching goals found in the 1990 National Resolution on the JFM are:

i. Providing an enabling mechanism for participation of local communities and a platform for NGO participation
ii. Facilitating institution building and allowed flexibility in their formation
iii. Eliminating the involvement of commercial interests and middlemen in the benefit-sharing mechanism
iv. Providing forest usufructuary benefits to participating communities
v. Providing for wage employment to local communities for some forest-related work
vi. Allowing for plantation of indigenous, multi-purpose species of trees and even grasses, shrubs and medicinal herbs
vii. Ensuring that the Forest Department only harvests in accordance with a working scheme prepared in consultation with local communities

The JFM Program gives village committees conditional access to a number of NTFP products and timber. The organization and conditions for membership vary across the different states. There are a number of variations in the JFM model. These variations are a result of differences in geography, resource base, socio-economic status, cultural diversity and the pressures on the forest. For example, Andhra Pradesh, Madhya Pradesh, Gujarat, and Orissa distributed 100% of the fuelwood harvested to the village committees, in Arunachal Pradesh it was 50% and West Bengal 25% (TERI 2000).

While there are many case studies of various facets of JFM and Social Forestry that provide useful insights into the micro-level aspects of the working of these programs, there are also regional studies (Bhat et al. 2001; Murali et al. 2002) that suggest that the JFM program could play a positive role in forest regeneration.

Growth of the JFM program in terms of hectares covered and the number of village forest committees and states

Figure IV.5 shows the growth in the JFM program in terms of hectares managed by the village committees. Though the JFM program began in 1990, data on the areas covered is available only since the end of 1990's. By the year 2000, JFM covered an area of 10.25 million hectares; this accounted for 39.22 percent of the open forest area (10% to 40% crown cover (Khare et al. 2000)) of 261,310 sq kms in India. Village committees in the country numbered 36,130 in 2002: JFM had covered 14.09 million hectares spread over 63,618 village committees in 27 states, about 50% of the degraded or open area (Murali et al. 2002, Damodaran and Engle 2003). By 2004, JFM covered 17.33 million hectares spread over 84,832 village committees and by 2010, the JFM program covered 22.96 million hectares managed by 105,323 village committees across 28 states and one union territory.

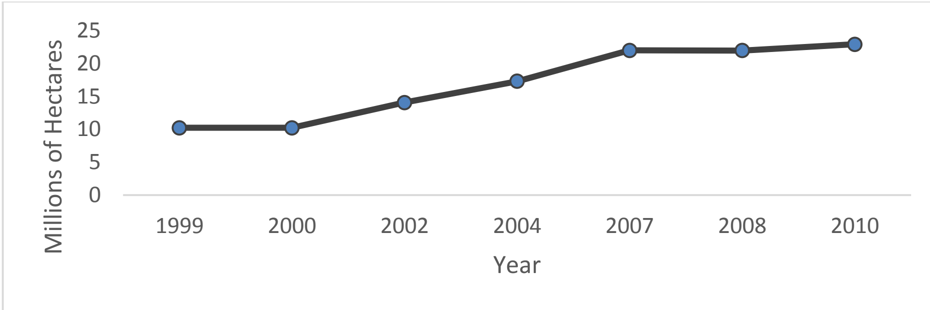

Figure IV.5. Forest Area under the JFM Program
Source: The Ministry of Environment and Forests Annual Reports (2001,2008,2009)and Compendiums of Environmental statistics (2003,2007,2013). State of Forest Reports(1999) and Damodaran and Engel (2003), Govt of India (2002)

The growth in JFM program has decreased since the end of the 2000's. This might be due to the lack of degraded forest or the lack of legislation that extended the JFM project to non-degraded forest areas. During this period, the forest cover of India stabilized as seen in figure IV.1.

The original JFM framework was criticized by Saxena (1992b) on a number of grounds. Legally, the status of the JFM committees was not defined. Moreover, there was a lack of policies that ensured the participation of women.

The state forest departments wielded too much power. This was exhibited in the monopsonistic (single buyer) power by government agencies for marketing NTFPs, lack of specific imbalance in power between the state forest department and communities, no special training for forest officers and no change in administrative ethos and restricted access by the village committees to NTFP and forest products.

The goals and policies of the State forest department were not well defined. There was a lack of coordination between JFM and other departments and programs.

The working plans of the state forest departments did not clearly integrate the JFM programs. While greater access to forest products could have provided incentives for forest conservation, the structure of the JFM program creates certain disincentives. The poor are net losers in these projects and have no incentives to protect the forests (Singh 2002). According to Behera and Engel (2006), who use Williamson's (2000) framework to analyze the efficiency of the JFM programs, the lack of transparency in the transfer of rights (for example legal ambiguity) creates disincentives for community participation. Further, their analysis also finds the information asymmetry and the rent-seeking activities of the state forest department undermine the efficiency of the system.

In 2002, The Government of India issued additional guidelines to promote greater uniformity in the implementation of the JFM program. These guidelines also addressed some of the observed deficiencies in the framework. The 2002 guidelines with regard to property rights led to the following amendments. Firstly, in an attempt to strengthen the property rights legal backup was provided to JFM committees. The management of the forest resources was also made inclusive by specifying certain quotas for women. Thirdly, by extending the JFM program to good forest areas, the property rights of the villages were now extended to these areas. The property rights of the forestry resources are now extended to include self-initiated groups, The 2002 guidelines focus on the legal relationship between the forest department and the village committees, the relationship between panchayats (village self-government councils) and the JFM committees and NTFP.

Studies also found evidence that political structures were crucial in the functioning of the JFM program (Lele 2000). Lawbuary 1999 and Saxena and Sarin 1999) find that no specific mechanisms to protect the private (excludable) goods are often captured by members of a village elite that might have already captured the decentralized village – level forest institutions Kumar (2002). The arrangements of the JFM program do not allow for the employment of the village committees. The state still exercises a considerable amount of power (Lele 2000).

The new guidelines issued by the government addressed certain aspects of the program. However, these guidelines did not specifically address the perceived deficiencies in the role of the state government except to state that the political neutrality of the village committee must be maintained. No provisions were made for the training of forest officers in the ethos of community forestry. The monopsony nature of the forest agencies was also not addressed. The de facto power of the Forest Departments actually leads to insecure property rights to forest resources.

Comparison between increases in forest area and areas under the Joint Forest Management Program

A large proportion of India's forests are under the JFM program. The impact of the program's effect on potential property rights on the forest resources is ambiguous. Mather (2007) and Bhat et al. (2001) suggest that the JFM program might have preserved forests. However, Puyravaud et al. (2010) suggest that natural forests continue to disappear at the rate of 1% annually.

Table IV.8. Percentage Changes in Areas under JFM and Forest and Open Areas (2004–2011)

States	Percentage Change in Area under JFM	Percentage Change in Forest Area	Percentage change in area under open forest
Andhra Pradesh	-19.44	2.56	-3.72
Arunachal Pradesh	-69.94	-0.09	-2.38
Assam	-32.85	-0.31	0.07
Bihar	158.78	0.56	35.25
Chhattisgarh	16.59	-0.46	-3.12
Goa	610.00	0.00	7.59
Gujarat	147.44	2.92	5.07
Haryana	7.14	0.10	5.94
Himachal Pradesh	45.97	0.25	-6.75
Jammu & Kashmir	-19.26	0.09	-10.28
Jharkhand	157.79	-0.66	-4.55
Karnataka	159.31	1.12	8.25
Kerala	1.48	-0.02	8.91
Madhya Pradesh	21.59	0.09	3.27
Maharashtra	89.45	-0.05	10.49
Meghalaya	0.00	-0.03	-28.20
Mizoram	317.76	0.81	4.19
Manipur	-16.41	0.41	-3.89
Nagaland	78.50	2.78	-9.99
Orissa	29.73	-2.54	1.47
Punjab*	252.87	0.30	23.11
Rajasthan	107.03	6.27	1.64
Sikkim	14653.00	0.47	-18.08
Tamil Nadu	61.74	0.06	-2.34
Tripura	275.36	1.33	1.82
Uttar Pradesh	-16.68	-2.40	0.06
Uttarakhand	-88.29	-0.06	-7.89
West Bengal	6.91	0.01	-15.43

Sources: State of the Forest Reports (2005 and 2011) and Compendiums of Environmental Statistics (2007 and 2013).

Table IV.8 examines the relationship between the percentage increase in forest area (2005 to 2011) and the percentage increase in areas under JFM (2004 to 2010). Since the JFM primarily focused on degraded areas, the relationship between percentage change in forest cover and percentage change in area under JFM are examined. This is mainly to take into account the changes in guidelines in the policy.

The correlation coefficients between these two indicators of forestry (forest cover and open forest cover) and areas under JFM are 0.0065 and -0.2725, respectively. These values are associated with p-values of 0.9738 and 0.1606**.** This suggests that the increase in JFM areas has very little association with the increase in forest areas. However, the stronger negative association between areas under the JFM program and open forest area suggests that the JFM program has led to a regeneration of the open forest.

Conclusion

The success of the Social Forestry Program in increasing plantation cover is generally well accepted (Saxena 1997). The dependence of forest-based industries on timber directly from natural forests has generally waned. One of the reasons is the supply of wood from Farm Forestry and also the supply of wood from exports. The Farm Forestry Component of the Social Forestry Program was successful in providing raw materials for forest-based industry. This increase in plantation cover could be the main reason for the stabilization of the forest cover rather than the regeneration of natural forests (Puyravaud et al. 2010).

The impact of the Social Forestry Program on NTFP products, especially fuelwood supply, is more ambiguous. Recent NCEAR and Foster and Rosenzweig's (2003) estimate suggest there could be a decrease in dependence on forest reserves for fuelwood. This could be based on both the availability of alternate substitutes, one of these alternatives being trees outside forests. However, other studies suggest that extraction of fuelwood continues to be one of the major causes of deforestation.

Kumar (2002), Mather (2007) and Bhat et al. (2001) suggest that the JFM program might have led to forest regeneration and hence the forest transition. There is a contemporaneous overlapping of the initiation in the JFM program of forest cover stabilization.

The government's focus shifted away from the revenues of the state forest departments towards the needs of the local populations. The impact of this proposed decentralization in forest policy on the forest transition is ambiguous. Most of the studies that suggest that the JFM program plays a role in forest regeneration are confined to specific geographical areas. The results of these studies cannot be generalized. There is considerable disparity in the power structures and implementation of the JFM program across states. This might play a role in its success.

Clarity of property rights, the incentives provided by market forces and certainty in demand for products could possibly be the largest motivators for the success of the Farm Forestry component of the Social Forestry Program. And conversely, the lack of clarity in property rights, the continued domination of the forest department and government agencies might hamper the effectiveness of both the community component of the Social Forestry and Joint Forest Management Programs.

CHAPTER V

CONCLUSION

All three essays in this thesis are concerned with the relationship between environmental degradation and welfare at the macro level. This analysis examines support for theoretical frameworks that attempt to explain the relationship between indicators of economic development and environmental degradation. It is an attempt to examine the empirical support for environmental theories that suggest that increases in welfare of a region provide incentives for increases in environmental quality.

The contribution of the first essay is to examine the relationship between agricultural extent and increases in agricultural productivity. One of the explanations for the forest transition theory is the Borlaug Hypothesis. The Borlaug hypothesis can be considered within the framework of Angelsen and Kaimowitz's theory. There have been many studies that examine the linkages between income and deforestation: these studies are interested in providing an empirical verification of the Environmental Kuznets Curve (EKC) hypothesis. Another contribution is the linking of AK literature with empirical EKC studies. Angelsen and Kaimowitz's analysis divides the causes of deforestation into underlying and immediate causes of deforestation. EKC regression analysis provides indicators and measures of these underlying causes of deforestation. These indicators are used, within AK's framework, to test certain implications. Combining the empirical framework of the EKC (specifically Barbier's (2001) specification) and the theoretical framework of AK, we are able to provide an empirical test for AK's theory on the effect of advances in agricultural change on forest area. Therefore, the first essay is in essence a synthesis of two broader frameworks. The theoretical and empirical framework of the EKC hypothesis examines the causes and economic incentives for deforestation.

Specifically, the first essay is concerned with explaining whether increases in agricultural productivity lead to incentives for reforestation. Easily accessible macro-level data are used to provide empirical support. These data are frequently used to provide empirical verification of the EKC hypothesis.

Although the empirical EKC literature focuses on the relationship between income and measures of environmental degradation such as pollution emissions, pesticide use and deforestation, its theoretical construct is concerned with the causal relationships between economic development and environmental degradation. Does economic development provide incentives for increases in environmental quality?

This is at its heart a causal question. This question provided the motivation for the second essay. The second essay is, therefore, an exploration into causation; however, it is tested empirically within the context of the EKC. A methodological tool, the DAG approach, is offered to reveal better insights into the nature of causation between variables. This methodology focuses on providing empirical support for particular theoretical definition of causality provided by Hume, the manipulative definition of causality rooted in contemporaneous time. The results of this approach are combined and contrasted with the Hume predictive definition of causality, empirically tested using the Granger Causality approach. It is hoped that the insights gained from both approaches provide a more complete picture of the nature of causality between variables. The DAG approach provides support for a direct causal relationship between income and pollution emissions. There is evidence to suggest that changing values of income lead to a change in the values of pollution emissions. Frequently employed datasets are used in this analysis.

The empirical techniques employed in this second essay are similar to the techniques employed in the first essay. Both essays deal with panel data across countries over sufficiently lengthy periods of time. The relatively lengthy periods of time suggest that time series issues such as the stationarity of the variables is of concern. Therefore, stationarity tests are carried out in both analyses. Further, time-series issues are closely related with establishing the causal relationship between variables.

The third and final essay is an exploration of the forest transition theory in the context of India. This analysis is closely linked with the first essay. Both essays are concerned with incentives for the forest transition. They both operate within theoretical frameworks for deforestation that owe a lot to the contributions of Angelsen and Kaimowitz's theories on deforestation.

The third essay is also based on Alexander Mather's work on the forest transition and particularly on the Asian forest transition. Evidence for various theories for forest transition is explored. On the basis of Mather's work, greater emphasis is placed on the two governmental programs: The Social Forestry Program and The Joint Forest Management Program. The objective is to examine whether growth in institutions and the move towards decentralization provide incentives for forest regeneration.

Empirical analysis is hampered by the lack of availability of data on these programs. Accessible and available data are used to examine the support for various theories of forest transition. The role of these and their role in the most plausible theory for forest transition are examined. Market forces and certainty seem to be the main forces driving the forest transition in India. However, government policy seems to have played a role in addressing these needs. The impact of decentralization appears to be ambiguous.

While the relationship between the second and the third essay might not be immediately apparent, both essays are based on macro theoretical frameworks that examine the relationship between economic incentives and environmental quality. The forest transition theory is also closely linked to the EKC for deforestation.

In conclusion, this thesis tries to provide empirical support for theoretical frameworks in Environmental Economics. The data employed for this study are macro-level datasets. The gathering of appropriate intermediate and micro-level data would provide the ability to test certain implications of these theoretical frameworks. This would strengthen the empirical basis for these theories. However, certain broad trends that might be useful for policy analysis such as the difference in impact of the various crops on agricultural land use and the unidirectional relationship from income to emissions might help guide policy.

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APPENDIX I

ANGELSEN AND KAIMOWITZ'S THEORETICAL FRAMEWORK

Introduction

The AK framework begins with assuming that there exists a production function

(A.I.1) $Y = \alpha F(N, A)$

where Y is the production function and N and A refer to the efficient levels of the two factors of production, labor and land. As in AK we assume that the production function exhibits constant returns to scale. This implies that the parameter, α, is a measure of pure yield, increasing technical change. The efficient levels of labor and land are actually defined by the functions $N = \varepsilon L$ and $A = \beta H$, where L is the total number of labor units utilized (for e.g., Man hours) and H is the physical number of land units utilized (for e.g., acres). The variables β and ε, both greater than 1, refer to the state of technology parameters associated with labor and land, so that as these variables decrease, efficiency increases.

The resulting yield function can be expressed in terms of Q, yield per efficient unit of land as a function of n, the efficiency units of labor per efficiency units of land.

(A.I.2) $Q = f(n),\ Q = \frac{Y}{A} = \frac{Y}{\beta H},\ n \equiv \frac{N}{A} = \frac{\varepsilon L}{\beta H} = \frac{\varepsilon}{\beta} l.\ l = \frac{L}{H},\ f_n > 0$ and $f_{nn} < 0.$

Technological Change at the Micro Level

The subsistence model

In AK's subsistence model, it is assumed that each farmer wants to generate a fixed amount of income $\bar{I}$ that meets their basic needs. The subsistence model may arise in three situations. The first situation is a condition in which the farmer's only desire is to consume a certain fixed amount of goods and services. The second situation arises when there are certain norms that state that any surplus the farmer generates must be shared. And the third and final condition arises when the output markets are not functioning properly. The third condition does not allow farmers to sell their produce and convert it into other types of consumer goods and services.

AK assumes that the area dedicated to agriculture forms a circle around a village and the outer limits of this circle is denoted by b^e. The farm gate price is $(p - tb)$, where b is the distance from the farm to the center of the village in kilometers and t is the measure of transport costs per acre. Further, it is assumed that the amount labor input per hectare in efficiency units is also fixed; $n = \bar{n}$, farmers cannot sell more than a fixed amount of labor $\overline{L^0}$ at a fixed wage rate w. The distance from the farm to the center of the village is denoted by b. The farmer's problem is to minimize effort subject to constraints on the minimum amount of output and a certain fixed amount of labor $\overline{L^0}$ at a wage rate w:

(A.I.3) $\text{Min}\int_0^{b^e} \bar{n}\beta\varepsilon^{-1}\, hbdb + \overline{L^0}$ subject to $\int_0^{b^e}(p - tb)\alpha f(\bar{n})\beta hbdb + w\overline{L^0} = \bar{I}; h \equiv 2\pi/K.$

Here K is the number of households in the village; therefore the expression $h = 2\pi/K$ represents the share of the circle available for each household.

In this model, with n fixed, both pure yield increasing technological change and labor-intensive technological advances will increase forest area, because the same income can be obtained from a smaller agricultural area. However, the labor-saving technological change will not change the rate of deforestation in this model; the only change is that the effort required to reach the subsistence level now decreases.

A perfect market (open economy) model

Assumptions under the perfect market open economy model are diametrically opposite to the subsistence model. In this model it is assumed that farmers can sell any amount of produce at the market price. There are no constraints on labor either, and the farmer is assumed to be indifferent between working on the farm or off the farm. Further, both family labor and non-family labor are assumed to be perfect substitutes for each other. The assumptions under the perfect market open economy model enable us to analyze decisions from a profit-making perspective. In the perfect market (open economy) model, the maximization condition is as follows:

(A.I.4) $(p - tb)\alpha f(n)\beta hb - wL$

The first order conditions that emerge from this maximization problem are equation A.I.4, marginal returns from labor must equal the marginal returns or profit from selling the product, and A.I.5 which represents the condition that it is profitable for a farmer to expand the agricultural frontier until land rents are zero:

(A.I.5) $(p - tb)\alpha f_n = w$

(A.I.6) $(p - tb)\alpha f - w/\beta^{-1} = 0.$

In this model, pure yield increasing or labor-saving technological progress (changes in α and ε) makes agriculture at the frontier more profitable and therefore leads to an increase in deforestation. However, labor-intensive technologies have no effect on deforestation (changes in β).

Technological Change at the Macro Level

The following models describe technological change at the macro level. The open economy model presented above can be viewed as a special case of the macro-level model, where changes in labor demand or output supply resulting from technological change are too small to influence wages or output prices. The macroeconomic models allow prices and wages to be endogenous. These two cases are presented below. In these models the agricultural sector consists of extensive and intensive sectors.

The basic idea between equations in these models is similar to the perfectly competitive model. The incentive once again is to maximize profit.

A model with endogenous wages

The model with endogenous wages makes the following assumptions. Firstly, the output prices are fixed. Secondly, the sector uses two inputs, land and labor, and finally, the total amount of labor is fixed in one of the sectors and not in the other. Additional land is perhaps brought into production, however, at an increasing cost.

The first order conditions for profit maximization in each sector in this model are similar to those derived within the open economy framework. However, an additional condition needs to be specified to account for the fixed labor supply. This condition creates the fixed labor supply. Farmers add labor in farm production as long as the value of the increased input is higher than the cost of labor:

(A.I.7) $$p^i \varepsilon^j \alpha^i f_n^j - w = 0; j = i, e,$$

where j refers to the sector involved (i = intensive, e = extensive).

The amount of land in the intensive sector is fixed $H^i = \overline{H}^i$. Deforestation is related only to the expansion of agricultural land in the extensive sector. The first order conditions in this sector are therefore similar to the open market economy. The extensive sector expands up to the point where land rent is zero,

(A.I.8) $$(p - tb^e)\alpha^e f^e - wl^e b^{e^{-1}} = 0.$$

Equation A.I.8 demonstrates that the total labor supply is fixed and allocated between two sectors (demand = supply); this condition is specified to ensure that there is full employment and the same wage in the two sectors.

(A.I.9) $$\overline{L} = L^e + L^i; L^e = \int_0^{b^e} l^e \, hbdb, h = 2\pi; L^i = l^i \overline{H}^i.$$

It is further assumed that employment in agriculture is small compared to rest of the economy. These four equations determine the labor inputs per hectare (l^i, l^e), the wage rate (w) and the outer edge of cultivation (b^e). The following table presents the effect of the various types of technological change in this sector.

Table A.I.1. Effect of Technological Change on Deforestation in a Model with Endogenous Wages

Type of technological change	Intensive sector	Extensive sector
Pure yield increasing technological change (α)	Decrease	Increase
Labor-intensive technological progress(β)	Decrease	Decrease
Labor-saving technological change (ε)	Increase	Increase

Source: Table 6.1 (Angelsen and Kaimowitz 2001) pg. When does technological change in agriculture promote deforestation?" D.R. Lee and C. B. Barret eds. in *Tradeoffs or synergies?*: agricultural intensification, economic development and the environment, reproduced with the permission of CAB International, Wallingford, U.K.

The effects of technological change depend on the type and the sector. In the case of the intensive sector, both yield increasing and labor-intensive technological progress will reduce deforestation. In the case of labor-saving technological progress, labor will be relocated from the intensive sector to the extensive sector, increasing deforestation.

In the extensive sector both yield increasing and labor-saving technological progress lead to an increase in deforestation. However, labor-intensive technological progress will simulate forest conversion.

A model with endogenous output price

In this model, AK assumes that the wage rate is exogenous. Changes in agricultural output induced by changes in technological changes are large enough to affect prices. Both the intensive as well as the extensive sector produce food for the same market.

The first three conditions of this model are identical to those of the previous model. However, wages rather than prices are endogenous. The equation for labor market equilibrium is now replaced with the condition for output market equilibrium, and it states that supply must equal demand:

(A.I.10) $$\alpha^i f^i \beta^i \overline{H}^i + \int_0^{b^e} \alpha^e f^e \beta^e h b db - \Upsilon E(p) = 0.$$

Demand is a function of price and this is represented by $E(p)$, and γ is a shift parameter, which can be used to study changes in demand. Supply is represented by the expression $\alpha^i f^i \beta^i \overline{H}^i + \int_0^{b^e} \alpha^e f^e \beta^e h b db$, the expression $\alpha^i f^i \beta^i \overline{H}^i$ represents quantity supplied by the intensive sector, and the term $\int_0^{b^e} \alpha^e f^e \beta^e$ represents quantity supplied by the extensive sector.

Any type of technological progress in the intensive sector will lead to an increase in production; this in turn will cause a downward pressure on prices, and therefore reduce land expansion in the extensive sector. Once again, in the extensive sector, labor intensive technological changes will reduce deforestation. The effect of pure yield increasing and labor-saving technologies in the extensive sector cannot be predicted by theory alone. If product demand is inelastic and the extensive sector has a high share of total output deforestation will be reduced. In other cases it will increase. The effect of a change in the technology on the agricultural frontier is derived on the basis of the first order conditions associated with each model. These results are summarized in table II.2.

APPENDIX II

STATIONARITY AND COINTEGRATION TESTS

Stationarity Tests

The Levin Lin Chu test

The null hypothesis under the Levin Lin Chu (LLC) (2002) test states that each of the series contain a unit root or are non-stationary versus an alternative hypothesis that each of the series are stationary. The test is carried out in three steps. In the first step an augmented Dickey Fuller test is run for the following equation for each of the cross-sections.

(A.II.1) $\Delta y_{it}=\rho_i y_{i,t-1} + \sum_{L=1}^{P_i} \theta_{iL}\Delta y_{i,t-L} + \alpha_{mi}d_{mt} + \varepsilon_{it}$, m=1,2,3

In the second step, two auxiliary regressions are run to obtain orthogonal residuals these two regressions are represented by the following equations:

(A.II.2) Δy_{it} on $\Delta y_{i,t-L}$ and d_{mt} to obtain the residuals $\hat{e}_{it}$ and

(A.II.3) $y_{i,t-1}$ on $\Delta y_{i,t-L}$ and d_{mt} to get residuals $\hat{v}_{i,t-1}$.

In the third step the residuals are standardized by dividing by the standardized error from each of the individual Dickey Fuller tests. This step is then completed by running the pooled Ordinary Least Squares (OLS) regression:

(A.II.4) $e^{-}_{it} = \rho v^{-}_{i,t-1} + \varepsilon^{-}_{it}$

where the null hypothesis is $\rho = 0$. This test is said to perform well when N lies between 10 and 250 and T lies between 5 and 250 (Nell and Zimmerman 2011).

Im, Pesaran and Shin (IPS) test

This test is less restrictive than the LLC test. In the LLC test it is assumed that the parameter ρ is homogeneous across all the cross-sections. This test can be considered as a generalization of the LLC statistic; it allows the parameter ρ to vary across individuals. The null hypothesis states that all individuals follow a unit root process:

(A.II.5) $H0{:}\rho_i = 0$ for all i

The alternate hypothesis allows some of the individuals, though not all, to have unit roots or be non-stationary. Both the LLC tests and the IPS tests vary from size distortions when N is either too small or too large relative to the size of T (Galeotti et al. 2009).

The test statistic t_p is an individual t statistic for testing the null hypothesis that ρ_i = 0 for all i; the test is based on averaging individual unit root tests $t^{-} = 1/N \sum_{i=1}^{N} t_{\rho_i}$, This statistic is asymptotically N(0,1) distributed (Nell and Zimmerman 2011).

Breitung's test

The Breitung test is similar the LLC test; however, it does not include deterministic terms in the first step (Nell and Zimmerman 2011).

Fisher's test

The Fisher-type test is proposed by Maddala and Wu (1999). The test statistic is:

(A.II.6) $$\mathrm{FTT} = -2\sum_{i=1}^{N} \ln p_i$$

The above test statistic is asymptotically Chi-square distributed with 2N degrees of freedom. p_i is the asymptotic p-value associated with the test of a unit root for the i^{th} individual. Both the IPS and fisher tests do not require a balanced panel dataset (Galeotti 2009).

Cointegration Tests

Pedroni test

The Pedroni (1999, 2004) test extends the Engle Granger's Framework. It is based on an examination of the residuals of spurious regressions which are performed using I(1) variables. If the variable are cointegrated, then the residuals should be I(0). However, if the residuals are not cointegrated, then the residuals should be I(1). Consider the following regression:

(A.II.7) $$y_{it} = \alpha_i + \delta_i t + \beta_{1i}x_{1\,i,t} + \beta_{2i}x_{2\,i,t} + \cdots .. + \beta_{Mi}x_{M\,i,t} + e_{i,t}$$

For t=1,…….T; I =1,……….,N: m=1………M, the residuals $e_{i,t}$ are assumed to be integrated of order one, e.g., I(1). The parameters α_i and δ_i are individual and trend effects, respectively. The general approach is to test if the residuals from the above equation are I(1) by running auxiliary regressions:

(A.II.8) $$e_{it} = \rho_i e_{it-1} + u_{it}$$

(A.II.9) $e_{it} = \rho_i z_{i,t-1} + \sum_{j=1}^{p_i} \phi_{ij} \Delta e_{i,t-j} + u_{it}$ (Eviews 2010).

The cointegration statistics can be divided into two classes; the first class (panel statistics) is based on a pooled estimate of $\phi_{i,}$ and the second class of statistics (group mean statistics) uses an average of the different $\phi_{i,}$ which is estimated separately for each individual. For the panel group of statistics, the alternative hypothesis is that the parameters are homogeneous. The group-mean statistics are against heterogeneous alternatives (Galeotti 2009). The test statistic is constructed from the residuals of either equation A.II.8 or equation A.II.9. It is shown that the statistic is asymptotically normally distributed (Eviews 2010).

Kao's cointegration test

The Kao (1999) coinegration test is similar to the Pedroni test. However it specifies cross-section specific intercepts and homogeneous coefficients on the first stage repressors. Equation A.II.7 is run, in this case however the α_i's are required being heterogeneous and the β_i are assumed to be homogeneous across cross-sections. The trend coefficient in equation A.II.7 is assumed to be zero.

Kao then runs a pooled auxiliary regression:

(A.II.10) $e_{it} = \rho_i e_{it-1} + v_{it}$

Or the augmented version:

(A.II.11) $e_{it} = \rho_i z_{i,t-1} + \sum_{j=1}^{p_i} \phi_{ij} \Delta e_{i,t-j} + v_{it}$

Under the null hypothesis the pooled specification is:

(A.II.12) $$\mathrm{DF}_{\rho} = \frac{T\sqrt{N}(\hat{\rho}-1)+3\sqrt{N}}{\sqrt{10.2}}$$

And for $p > 0$ (i.e., the augmented version) converges to N (0, 1) asymptotically (Eviews 2010).

Westerlund cointegration tests

The Westerlund tests assume the following data-generating processes. These tests are based on error correction.

(A.II.13) $$\Delta y_{it} = \delta_t' d_t + \alpha_i (y_{i,t-1} + \beta_t' x_{t,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j}$$

$$+\sum_{j=-q_i}^{p_i} \Upsilon_{ij} \Delta x_{i,t-j}$$

Where:

Y is the dependent variable

x is the vector of independent variables

$d_t = (1, t)'$ is the set of deterministic components and

Δ is the first difference operator

(Westerlund 2007) in (McCarl et al. 2009)

Four statistics are calculated; two of these are group statistics and the remainders are pooled statistics. Under the group statistics test, the null hypothesis is that $\alpha_i = 0$ is tested versus the alternate hypothesis that H1: $\alpha_i < 0$ for at least one i. These statistics are a weighted average of the individually estimated α_i and their t ratios, respectively. The pooled statistics combine information over from each and every cross-sectional unit. The null and the alternate hypothesis are $\alpha_i = 0$ $\alpha_i < 0$, respectively. Rejection of the null hypothesis suggests evidence of cointegration for the panel as a whole (Westerlund 2007).

APPENDIX III

ALTERNATIVE ESTIMATIONS ESSAY 1

Fixed Effects Estimator

The fixed effects model specification utilized by Barbier (2001) to estimate the effects of the variables on change in rate of agricultural extent is also utilized here. The fixed effects model is represented by the following equation:

(A.III.1) $$\mathrm{y_{it}} = \mathrm{X_{it}}\beta + \mathrm{i}\alpha_i + u_{it}$$

The fixed effects model is also referred to the Least Square Dummy model (LSDV) (Greene 1997). This model is a classical regression model, where it is assumed that the standard errors are identically distributed. However, in this case the standard errors are both heteroskedastic as well as correlated, prompting the use of robust standard errors. The Hausman test was employed to check if we should employ random effects or fixed effects estimation; the estimates observed under the random effects method revealed that the random effects estimators were equal to the OLS estimators, therefore the need for including fixed effects within the OLS framework were tested for. One of the drawbacks of the fixed effects model specification is that it does not take into account the non-stationary nature of the data. Non-stationarity data could lead to spurious regressions, necessitating tests for stationarity of the data.

Table A.III.1. The Fixed Effects Model with Normal Standard Errors

	Combined	Latin America	Asia
RY	-1.56E-07	7.80E-09	-7.26E-08
	(0.31)	(0.97)	(0.74)
WY	2.39E-07	8.45E-07	-2.30E-07
	(0.17)	(0.00)	(0.24)
MY	2.72E-07**	1.85E-07	-9.70E-08
	(0.04)	(0.42)	(0.51)
ARPP	-0.0051764	-0.019645	0.009779
	(0.75)	(0.39)	(0.67)
CRPL	-0.0070082***	-0.008299	-0.001494
	(0.00)	(0.00)**	(0.43)
PGDP	-1.83E-06**	-3.35E-06	-1.40E-06
	(0.03)	(0.20)	(0.02)
PGDPS^2	2.370E-10	1.09E-09	1.23E-10
	(0.16)	(0.39)	(0.27)
PPGDP	-0.0002378	-0.0003585	9.81e-06
	(0.19)	(0.17)	(0.96)
RITR	-0.0000342	-0.000565	.0001219
	(0.93)	(0.47)	(0.71)
WATR	-0.0003091	-0.000466	-.003656
	(0.67)	(0.59)	(0.33)
MATR	-0.0000167	0.000282	.0012414
	(0.98)	(0.68)	(0.58)
PPON	0.003667	0.009482	-.0023905
	(0.12)	(0.02)**	(0.23)

Notes: RY- Rice yield per hectare in Hg; WY- Wheat yield per hectare in Hg; WY- Wheat yield per hectare in Hg; MY- Maize yield per hectare in Hg; ARPP- Arable land (hectares per person; CRPL - Permanent cropland (% of land area); PGDP-GDP per capita (constant 2000 US$) (centered) data; PGDP^2 -GDP per capita(constant 2000 US $) squared; PPGDP- GDP per capita growth (annual %); PPON- Annual percentage change in population; RITR Rice export value US$ divided by income: WHTR- Wheat export value US$ divided by income; MHTR- Maize export value US$ divided by income.

Table A.III.2. The Fixed Effects Model with Robust Standard Errors

	Combined model	Latin America	Asia
RY	-1.56E-07	7.80E-09	-7.26E-08
	(0.34)	(0.97)	(0.74)
WY	2.39E-07	8.45E-07	-2.30E-07
	(0.45)	(0.18)	(0.32)
MY	2.72E-07	1.85E-07	-9.70E-08
	(0.06)	(0.21)	(0.58)
ARPP	-0.0051764	-0.019645	0.009779
	(0.80)	(0.49)	(0.73)
CRPL	-0.0070082***	0.008296	-0.001494
	(0.00)	(0.01)	(0.61)
PGDP	-1.83E-06**	-3.35E-06	-1.40E-06**
	(0.03)	(0.38)	(0.01)
$PGDPS^2$	2.37E-10***	1.09E-09	1.23E-10
	(0.03)	(0.25)	(0.06)
PPGDP	-0.0002378	-0.000359	9.81e-06
	(0.30)	(0.24)	(0.97)
RITR	-0.0000342	-0.00565	.0001219
	(0.89)	(0.30)	(0.41)
WHTR	-0.0003091	-0.000470	-.003656
	(0.23)	(0.17)	(0.10)
MATR	-0.0000167	0.000282	.0012414
	(0.96)	(0.58)	(0.12)
PPON	0.003667	0.009600	-.0023905
	(0.22)	(0.07)	(0.00)

Notes: RY- Rice yield per hectare in Hg; WY- Wheat yield per hectare in Hg; WY- Wheat yield per hectare in Hg; MY- Maize yield per hectare in Hg; ARPP- Arable land (hectares per person; CRPL - Permanent cropland (% of land area); PGDP-GDP per capita (constant 2000 US$) (centered) data; $PGDP^2$ -GDP per capita(constant 2000 US $) squared; PPGDP- GDP per capita growth (annual %); PPON- Annual percentage change in population; RITR Rice export value US$ divided by income: WHTR- Wheat export value US$ divided by income; MHTR- Maize export value US$ divided by income.

The Feasible Generalized Least Squares Model

The FGLS method is utilized when the variance covariance matrix is not spherical. The variance covariance matrix was found to be heteroskedastic as well as correlated. The estimating equation for the feasible generalized least squares is given by the following equation:

$$(\mathrm{A.III.2}) \quad (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}Y$$

where the equation for the variance covariance matrix is given by the following equation:

$$(\mathrm{A.III.3}) \quad (X'\Omega^{-1}X)^{-1}$$

The variance-covariance matrix is not known and is therefore estimated by the expression omega hat. The feasible least squares estimator was first applied to panel data by Parks (1967). The FGLS method performs well in large samples; it is equivalent to full maximum likelihood (Beck and Katz 1995).

There have been criticisms of the feasible generalized least squares method in the recent past (Beck and Katz 1995). The main criticism was that the feasible generalized least squares method tends to underestimate the standard errors of the estimators. However the accuracy of the feasible generalized least squares estimator increases as the ratio of T/N increases. For both the Latin American and Asian specifications of the model, the ratio T/N is greater than 4, and in the case of the combined model it is more than 3.

Table A.III.3. The Feasible Generalized Least Squares Model

	Combined	Latin America	Asia
DLNRY	-.0016001	.0010125	-.0043955
	(0.63)	(0.81)	(0.49)
DLNWY	.0024264	.0038064	-.0028174
	(0.28)	(0.15)	(0.59)
DLNMY	.001019	.001807	-.0007307
	(0.66)	(0.54)	(0.85)
DLNARPP	.1337372***	.0919349***	.3442101
	(0.00)	(0.00)	(0.00)
DLNCRPL	.0182918**	.0377507**	.0121853
	(0.04)	(0.03)	(0.20)
DLNPGDP	-.0067424	-.0031495	-.0248764
	(0.47)	(0.82)	(0.12)
DLNPGDPS^2	-.0000881	-.0000775	-.0002458
	(0.73)	(0.80)	(0.62)
DLNPPGDP	-.0024572	-.0017238	.0071609
	(0.76)	(0.88)	(0.59)
DLNRITR	-.0063121	.014996	-.017365
	(0.87)	(0.79)	(0.74)
DLNWHTR	.0000657	3.28e-06	.0000771
	(0.73)	(0.99)	(0.74)
DLNMATR	-.0375934	-.0391795	-.2549412
	(0.28)	(0.30)	(0.30)
DLNPPON	.0542309	3076204	.1528653
	(0.86)	(0.69)	(0.69)

Notes: RY- Rice yield per hectare in Hg; WY- Wheat yield per hectare in Hg; WY- Wheat yield per hectare in Hg; MY- Maize yield per hectare in Hg; ARPP- Arable land (hectares per person; CRPL - Permanent cropland (% of land area); PGDP-GDP per capita (constant 2000 US$) (centered) data; PGDP^2 -GDP per capita(constant 2000 US $) squared; PPGDP- GDP per capita growth (annual %); PPON- Annual percentage change in population; RITR Rice export value US$ divided by income: WHTR- Wheat export value US$ divided by income; MHTR- Maize export value US$ divided by income. The operator DLN refers to the log and first difference.

APPENDIX IV

LIST OF COUNTRIES INCLUDED IN STERN AND COMMON (2001)

(SC DATASET)

OECD

Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, Turkey, UK, USA, West Germany.

Non-OECD

Algeria, Argentina, Barbados, Bolivia, Brazil, Chile, China, Colombia, Cyprus, Czechoslovakia, Egypt, Ghana, Guatemala, Honduras, Hong Kong, India, Indonesia, Iran, Israel, Kenya, Korea, Madagascar, Malaysia, Mexico, Morocco, Mozambique, Myanmar, Namibia, Nicaragua, Nigeria, Peru, Philippines, Romania, South Africa, Saudi Arabia, Singapore, Sri Lanka, Syria, Taiwan, Tanzania, Thailand, Trinidad & Tobago, Tunisia, Uruguay, USSR, Venezuela, Yugoslavia, Zaire, Zambia, Zimbabwe.

APPENDIX V

IMPULSE RESPONSE FUNCTIONS AND SKEWNESS AND KURTOSIS TESTS

Figures

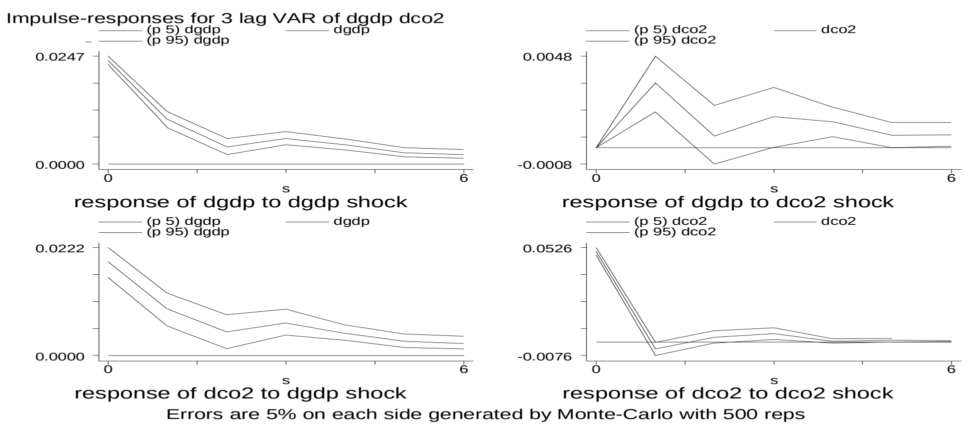

Figure A.V.1. Impulse Response Function DV Carbon Dioxide Data

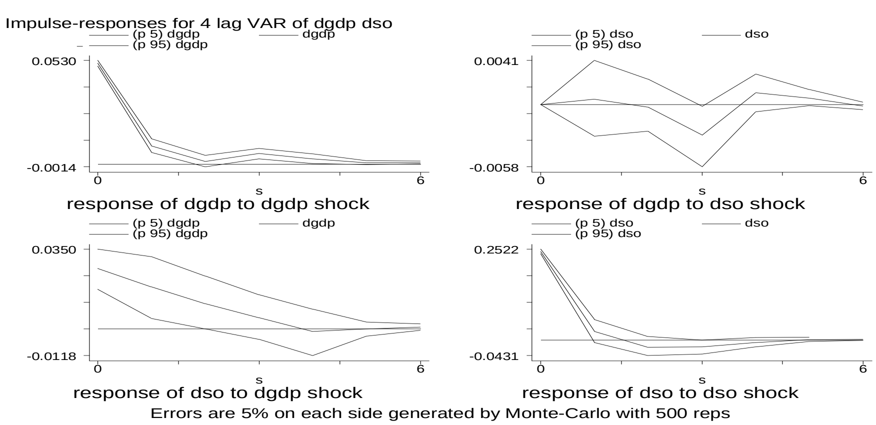

Figure A.V.2. Impulse Response Function SC Sulfur Dioxide Data

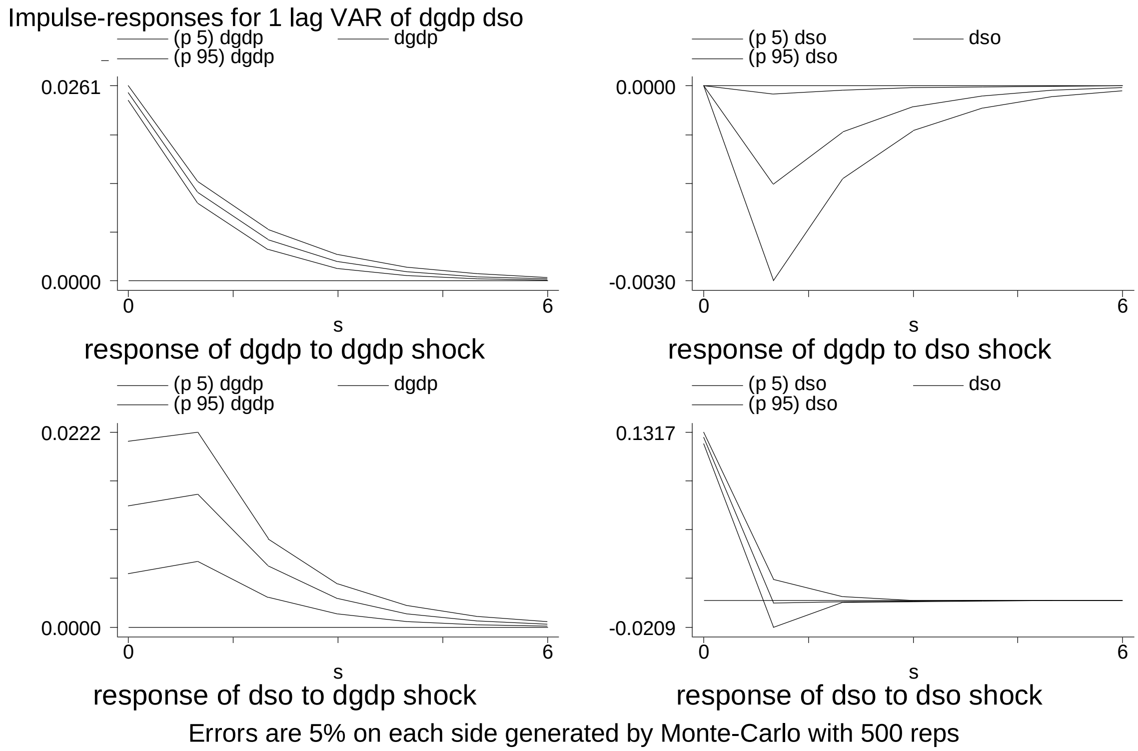

Figure A.V.3. Impulse Response Function DV Sulfur Dioxide Data

Skewness and Kurtosis Test

Table A.V.1. Results of the Skewness and Kurtosis Test

H0: The Residuals are Normally Distributed (DV Data Carbon) (P Values)

	Skewness	Kurtosis	Joint
GDPres	0.000	0.000	0.000
Co2res	0.000	0.000	0.000

Table A.V.2. Results of the Skewness and Kurtosis Test

H0: The Residuals are Normally Distributed (DV Data Sulfur) (P Values)

	Skewness	Kurtosis	Joint
GDPres	0.000	0.000	0.000
So2res	0.000	0.000	0.000

Table A.V.3. Results of the Skewness and Kurtosis Test

H0: The Residuals are Normally Distributed (SC data) (P Values)

	Skewness	Kurtosis	Joint
GDPres	0.000	0.000	0.000
So2res	0.000	0.000	0.000

Table A.V.4. Results of the Skewness and Kurtosis Test

H0: The Variables are Normally Distributed (DV Data Carbon) (P Values)

	Skewness	Kurtosis	Joint
lnGDP	0.000	0.006	0.000
lnCo2	0.000	0.000	0.000

Table A.V.5. Results of the Skewness and Kurtosis Test

H0: The Variables are Normally Distributed (DV Data Sulfur) (P Values)

	Skewness	Kurtosis	Joint
lnGDP	0.000	0.000	0.000
lnSo2	0.028	0.000	0.000

Table A.V.6. Results of the Skewness and Kurtosis Test

H0: The Variables are Normally Distributed (SC Data) (P Values)

	Skewness	**Kurtosis**	**Joint**
lnGDP	0.000	0.000	0.000
lnSo2	0.016	0.000	0.000

Granger Causality Tests

An alternate test of Granger causality is also applied[21]. These results are based on the initial panel models estimated by equation III.17, which are the unrestricted models. Assuming the lag length is correctly specified, "the variable X is said not to Granger cause the variable Y if the coefficients of X are not significantly different from zero" (Al-Iriani 2006). Therefore, a test for the presence of Granger causality is a test of the joint hypothesis that the coefficients of X are equal to zero. The test statistic follows a chi-square distribution with p degrees of freedom[22].

The residual sums of squares from both models are calculated; a chi-square test is then applied to test for the presence of Granger causality. The results of these Granger causality tests are presented in table A.V.7. The lag lengths chosen for these models are

[21] Problems with this test are described by Giles 2013; however, this test directly uses the results from the PVAR.

[22] A Wald test statistic is computed. The test statistic W=N (rss-uss)/(uss) $\sim \chi^2$ with p degress of freedom, where p = the number of lags.

based on the SBC criterion and are, therefore, identical to the lag lengths chosen for the initial panel VAR models presented in table III.9.

From table A.V.7 it is apparent that there is a bidirectional causal relationship between carbon dioxide emissions and GDP for DV's dataset. At the one percent level of significance, there is a unidirectional causal relationship between emissions and GDP per capita, for the sulfur datasets. At the 10 % level of significance we find evidence of a bidirectional relationship.

Table A.V.7. Panel Granger Causality Tests (Holtz-Eakin et al. 1988)

Null Hypothesis	**DV dataset carbon dioxide emission**	**DV dataset sulfur dioxide emissions**	**SC dataset Sulfur dioxide emissions**
Carbon dioxide does not Granger cause GDP	20.880***[23]		
GDP does not Granger cause carbon dioxide	45.144***		
Sulfur dioxide does not Granger cause GDP		3.729*	10.027*
GDP does not Granger causes Sulfur dioxide		17.753***	14.066**

Note:***,**, and * represent significance at the 1%, 5% and 10% levels; standard errors are reported in parentheses.

[23] The values in table A.V.9 correspond to the W statistic.